

A Multi-Agent Simulation Approach to Farmland Auction Markets: Repeated Games with Agents that Learn

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by
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ABSTRACT

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A Multi-Agent Simulation Approach to Farmland Auction Markets: Repeated Games
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The focus of this thesis is to better explore and understand the effects of agent interactions, information feedback, and adaptive learning in a repeated game of bidding in farmland auction markets. This thesis will develop a multi-agent model of farm-land auction markets based on data from the Saskatchewan Dark Brown Soil Zone of the Canadian Prairies. Several auction types will be modeled and data will be gathered on land transactions between farm agents to ascertain which auction type (if any) is best suited for farmland markets. Specifically, the model gathers information for 3 types of sealed-bid auctions, and 1 English auction and compares them on the basis of efficiency, price information revelation, stability, and with respect to repeated bidding and agent learning.

The effects of auction choice on macro-level indicators, such as farm exits, retirement, financial stability, average productivity, farm size, and participation were unknown at the outset of this thesis because of the complex dynamic nature of the environment. I find that the chosen learning mechanism employed here affects both price and variance of prices in all auctions. I also find that the second-price-sealed-bid auction generates the most perceived surplus, most equitable share of surplus, and also decreases uncertainty in the common-value element of prices. *A priori* it was believed that auction choice would have an impact on pricing efficiency, price levels, and shares of surplus generated from auctions as predicted by theoretical works. Surprisingly, auction choice does not influence market structure or evolution.

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LIST OF ABBREVIATIONS

ABBREVIATION	NAME	FIRST REFERENCE
ACE	Agent-Based Computational Economics	6
CRRAM	Constant Relative Risk Aversion Model	24
D/A Ratio	Debt to Asset Ratio	91
DAI	Distributed Artificial Intelligence	6
DARA	Decreasing Absolute Risk Aversion	20
FFS	Farm Financial Survey	57
FPSB	First-Price-Sealed-Bid	19
GE	Genetic Algorithm	28
IARA	Increasing Absolute Risk Aversion	20
IID	Identically, Independently, Distributed	19
LDT	Learning Direction Theory	24
MAS	Multi-Agent Simulation	2
MC	Marginal Cost	66
NCFBI	Net Cash Flow Before Investment	43
P	Price	66
RET	Revenue Equivalence Theorem	15
RNNE	Risk Neutral Nash Equilibrium	24
SPSB	Second-Price-Sealed-Bid	19
TPSB	Third-Price-Sealed-Bid	53
WTA	Willingness to Accept	44
WTP	Willingness to Pay	44

CHAPTER 1

INTRODUCTION

1.0 Introduction

Canadian farmers have witnessed a steady upward trend in farmland prices since January of 2000. Increases in some provinces have been as high as 8.2%¹, while Saskatchewan farmland has been increasing in value at a rate of approximately 1% semi-annually for the past 5 years².

The steady increase is thought to be driven by high grain prices stemming from demand from the biofuels industry and interest from out-of-province buyers. This demand, coupled with access to credit and low interest rates has helped maintain farmland prices in the face of rising input costs³.

In order for farmers, policy makers, and industry stake-holders to make informed decisions about investments and expectations, it is important to understand both the macro- and micro-economic factors that affect farmland prices and efficiency. Pricing efficiency in agricultural sectors is believed to be one of the key factors for competitive industry since farmland represents 21-25% of fixed costs and is the only true fixed factor in production (Ebmeyer and Schoney 2007).

Optimal farmland pricing is essential because overpriced farmland can cause financial weakness and divert funds from areas with higher returns on investment. Alternatively, underpriced farmland may cause some land to gravitate away from its highest and best use and away from the most efficient producers.

¹ Farm Credit Canada Spring 2007 Farmland Values Report: <http://www.fcc-fac.ca/en/Products/Property/FLV/Spring2007/index.asp>

² Ibid

³ Ibid

This thesis will focus on the dynamics of farmland auction markets. It will incorporate elements of heterogeneity, feedback, strategic bidding and learning into traditional static auction models. In so doing, we will uncover the effects of agent-level specific decision making processes on the macroeconomic model for farmland markets, something that has yet to be considered in the literature. Furthermore, a variety of auction types will be compared to determine which is best suited to selling farmland based on pricing efficiency and surplus generation.

I contend that the classic economic theory alone cannot adequately describe the land auction process since optimizing strategies and rational choice cannot completely explain the actions of individuals involved in the bidding process. And although rational choice and optimization lend themselves to deduction, the model is not fully specified. Rather, I assume that agents use adaptive behaviour, in conjunction with rational choice and optimization. In order to fully understand prices and pricing efficiency, the market must be modelled as an evolutionary process incorporating information sharing, heterogeneity, dynamics, uncertainty, complexity, space, and time. Only when the process is properly modelled will there be a fuller understanding of farmland markets.

To date there has been no attempt to model farmland auctions in this manner. While there have been prior attempts to model farmland auctions using a Multi-Agent Simulation (MAS) (Balmann 1997, Freeman 2005), such modeling was not the focus of their efforts and several important factors were not included. Unlike these papers, I will examine the effects of auction choice on market structure and efficiency. For example, farm exits, financial stability, productivity, price levels, transaction surplus, and price variability will be tracked to determine which auction mechanism is best suited for selling farmland.

This research also differs markedly significantly from anything done thus far because it incorporates time and space into the farmland auction framework. Some papers (Balmann 1997, Freeman 2005) have modeled “auction-like” land markets that incorporate time and space. Others have modeled farmland auctions (Colwell and

Yavas 1994). However, no one has yet combined a realistic farmland auction market with a dynamic model that includes space and time. Accordingly, this thesis is novel in that it provides both the proper context (farmland auction markets) and dynamic properties of space and time.

1.1 Objectives

The focus of this research is to better explore and understand the effects of agent interactions, information feedback, and adaptive learning in a repeated game of bidding in farmland auction markets. This thesis will develop a multi-agent model of farm-land auction markets based on data from the Saskatchewan Dark Brown Soil Zone of the Canadian Prairies. Several auction types will be modeled and data will be gathered on land transactions between farm agents to ascertain which auction type (if any) is best suited for farmland markets. Specifically, the model gathers information for 3 types of sealed-bid auctions, and 1 English auction and compares them on the basis of efficiency, price information revelation, stability, and with respect to repeated bidding and agent learning.

The effects of auction choice on macro-level indicators, such as farm exits, retirement, financial stability, average productivity, farm size, and participation were unknown at the outset of this thesis because of the complex dynamic nature of the environment. I find that the chosen learning mechanism employed here affects both price and variance of prices in all auctions. I also find that the second-price-sealed-bid auction generates the most perceived surplus, most equitable share of surplus, and also decreases uncertainty in the common-value element of prices. *A priori* it was believed that auction choice would have an impact on pricing efficiency, price levels, and shares of surplus generated from auctions as predicted by theoretical works. Surprisingly, auction choice does not influence market structure or evolution.

Interestingly, some of my findings support traditional theory (e.g. second-price auction performance), while others shed light on previously unknown areas of auctions and land markets (e.g. market structure and evolution).

1.2 Motivation for Study

Recently, MAS has become the tool of choice for researchers seeking an inexpensive experimental ‘laboratory-like’ setting to explore complex, dynamic systems of interacting agents. To date, MAS has been used by researchers in many of the physical sciences, including mathematics, biology, and chemistry with great success and is widely accepted in the literature as a valid tool for scientific analysis (Axelrod 2003).

MAS has primarily been used by economists to examine large macroeconomic systems comprised of non-linear equilibrium conditions and disequilibrium processes. MAS is particularly useful in such scenarios because it can capture “emergent⁴” phenomena and out-of-equilibrium behaviour (Gintis 2005). These emergent, or otherwise inexplicable dynamic properties of a model, can be valuable tools in methodological advancement of policies and theories in economics that cannot occur in classical economic analysis (Tesfatsion 2005).

In light of the insight generated by MAS models, agricultural economists have begun using it to model processes in the agricultural sector. Some of these topics include regional structural change (Balmann 1997, Freeman 2005), technology diffusion and resource usage (Berger 2001), and land-use management (Polhill et al. 2001).

This research will contribute to the literature in at least two ways. Firstly, I will extend the work on farmland auction markets to include heterogeneous agents, learning, feedback, and agent interactions. Secondly, I will apply MAS to auction theory in a manner that has yet to be attempted in the literature. This includes making assumptions about information and decision parameters that reflect real-world behaviour.

Much of the MAS based farm land auction work that currently exists (e.g. Balmann 1997, Freeman 2005) assumes an extremely simple auction environment without feedback and learning. To their credit, the auction mechanisms included in these models were designed to be simple in order to allow for a macro model that functioned as smoothly as possible. Since our model will focus exclusively on auction

⁴ A detailed description of emergent phenomena will be given in subsequent chapters.

mechanisms, this aspect of farm operations will be significantly more detailed and better capture the essential decision making elements of real-life land auction markets. I propose that it is the rudimentary agent-level components of the decision making process that drive the observable macro-level results in these land markets.

1.3 Thesis Organization

This thesis is divided into 7 chapters. This first chapter serves as an introduction to the issue. The second chapter will review the relevant literature on auction theory, agent-simulation, and land markets. Chapter 3 develops the structural model and equations that underlie the simulation. Chapter 4 discusses the data used for initialization. Chapter 5 outlines the criterion by which the auctions will be compared and measured. Chapter 6 provides the results and Chapter 7 concludes and discusses limitations to the model and future research.

CHAPTER 2

REVIEW OF LITERATURE

2.0 Introduction

This chapter will serve as a review of the literature to familiarize the reader with the basic concepts of MAS, Farmland Markets, and Classical Auction theory. The remainder of this thesis will be based on the concepts discussed here.

2.1 Introduction to Multi-Agent Simulations (MAS)

This section introduces the basic concepts and terminology used in MAS. MAS is one of many names for a set of modeling techniques used to explore phenomenon in the realm of distributed artificial intelligence (DAI). Agent-based Computational Economics (ACE) is an alternative name for the computational studies of economies modelled as evolving systems of autonomous interacting agents (Tesfatsion 2002). MAS and ACE research seeks to understand why certain global regularities have persisted in decentralized economies despite the absence of top-down planning. In effect, MAS and ACE use a bottom-up approach to explain these global regularities by modelling the repeated local interactions of autonomous agents acting on simple rules (Tesfatsion 2002). The following will discuss simulation in a more general context, covering a comparison of simulation to experimental economics, heterogeneity and simulation, as well as learning and information feedback in simulation. The chapter will close with a discussion of some challenges faced by researchers when using MAS. For the interested reader, a detailed introduction to MAS and ACE can be found in Tesfatsion (2002).

2.1.1 Simulation: An Alternative to Reductionism

Much of what is known about science is a result of using reductionism - studying the components of a system in an attempt to figure out how the system works as a whole. The limitation of this method is that systems are often larger (and more complex) than the sum of their parts. This idea is referred to as *Holism* and was first summarized by Aristotle in *Metaphysics*. Holism arose from the view that much of the world is not machine-like and many systems are inherently complex.

In light of this, recent research on complex systems⁵ is based on a common goal of understanding how a system can be characterized with respect to its individual components in a non-reductionist manner (Manson 2001). Simulation is one means by which to do this. Traditionally, models of systems are simpler than the system itself; models make assumptions that allow for the removal of component interactions that do not affect (or that are believed not to affect) variables of interest. Simulation models on the other hand, can be as complex as the system that they represent. In many cases, researchers can only observe one state of the system, but by using simulation, they are able to create hypothetical situations under which various states can exist.

Simulation is often used to model complex systems that seem to portray self-organization characteristics that could not have been foreseen by examining the elements of the system. The idea of self-organizing systems was made popular in economics by Adam Smith and his *invisible hand* guiding the economy (Smith 1776). Self-organizing systems are often described as adaptive, dynamic, and emergent, three concepts that will be highlighted in subsequent chapters (Tsfatsion 2001).

2.1.2 Simulation versus Experimental Economics: Why Use MAS?

Experimental economics has gained popularity as an economic methodology because classical economic analysis techniques are limited to examine only a subset of all possible exogenous “influences”. In contrast, experimental methods rely on controlled laboratory settings to test economic theories by controlling the number of influences.

⁵ Complex systems will be discussed in greater detail in subsequent sections.

Experiments in economics are often constructed to capture data about preferences and examine if those preferences actually influence economic decisions.

In general, experimental methods have generated considerable insight into human behaviour. There are a few problems with experimental economics as a methodology however. The most significant problem with economic experiments is that it is never possible to know *exactly* why a person has made a particular decision. Rather the individual's beliefs and preferences must be inferred from the choices she has made (Tesfatsion 2002). Also, human heterogeneity raises theoretical problems. That is, if individuals differ, similar experimental treatments can lead to different observed behaviours. An analysis of the aggregate effect could then suggest that a variable is irrelevant, since positive and negative effects cancel each other out, while the "mean agent" effect of the variable may not make rational sense (Novarese 2003).

To summarize, possible problems associated with experimental economics specific to this research program are:

- Data generation is limited to the number of participants
- Costly
- Time consuming
- Limited control over utility function or risk aversion factors
- Limited control over learning process and rate of learning
- Strategies and rules may not always be understood by all participants in complex games
- Very difficult (impossible?) to achieve asymptotic results
- Difficult to ensure all control parameters are in fact controlled

Learning and a lack of asymptotic results are particularly serious issues with respect to this thesis. As previously noted, agent learning is one of the key features of this research that helps to improve upon previous farmland auction models. Adjusting the learning process will go a long way to understanding the salient features of the decision process that affect bids and subsequent outcomes. Furthermore, it is important that asymptotic results are available to ensure that a valid trend in the data is observed, and the proper limit behaviour is deduced.

MAS modeling offers solutions to many of the problems associated with experimental methods. As we shall see, advantages to using MAS models include:

- Asymptotic results are generally easy to achieve
- MAS is relatively cheap
- Offers control over parameters
- Logical flow: No “black box” element
- All agents understand the rules of the game and the decisions available to them
- Learning, and learning rates, can be controlled to compare a variety of alternate conditions
- Long trial periods do not become tedious for agents
- Once initial conditions are set and model evolution occurs, we can often trace the path of evolution back to the root cause in the initial parameters
- Risk aversion factors are known and can be controlled
- Utility functions can be based on classical economic theory and results from experimental economics

2.1.3 Heterogeneity

The issue of individual heterogeneity and its impact on economic systems has received considerable attention in the literature. In standard economic models, heterogeneity is typically introduced in a very structured manner whereby individual characteristics are drawn from a set of known values. However, assumptions like this can be problematic because any variance in individual behaviour is necessarily small and behaviour is very predictable. Moreover, in order to keep models tractable, it is commonly assumed that heterogeneity among agents does not change over time. Parker et al. (2003) note that heterogeneity across real agents can manifest in their biophysical environment, in their values, their ability, and their resources. Note that these characteristics can change over time as a result of learning and environmental changes. The literature is also quick to note that when heterogeneity and interdependencies (feedback) are combined, traditional analytical solutions are nearly impossible to attain⁶.

Within the scope of MAS models, it is crucial to understand the importance of heterogeneity. Novarese (2003) suggests that it is the underlying heterogeneity of

⁶ See Sections 2.1.4 and 2.1.5 for more information.

human agents that has led to so misunderstanding of theoretical and empirical economic research. He suggests instead that hypotheses should not be posed and accepted but tested and verified. The only way to accomplish this is to understand the implications of differences between economic agents, and not simply assume away true heterogeneities for tractability. Novarese (2003) also notes that this goal will require new instruments of analysis. In this light the ability of MAS to model complex systems of heterogeneous agents has been well documented in the literature (Teshatsion 2000, 2001, and 2002, Parker et al. 2003, and Janssen 2005) and as such, offers advantages over classical economics and experimental methods in the study of human behaviour.

2.1.4 Agent Learning and Information Feedback

The issue of learning in economic theory is one that has only just recently begun to receive attention. Mainstream studies in economics often assume simple interactions of unboundedly rational agents that instantaneously achieve a common consistency – usually a Nash best response. Classically, this method sufficed for shedding light on the salient features of the model at hand, and the related outcomes (Friedman 1998).

Evolutionary economics on the other hand (of which MAS is a subset) emphasizes the importance of adaptation processes of boundedly rational, imperfectly informed agents. These models do not assume that all agents have common, perfect knowledge about the strategies and information of all other agents. Clearly, agents in a well designed MAS may have incomplete information about the preferences and rationality of other agents. As such, formally computing equilibria can be extraordinarily difficult and choosing an equilibrium concept can be equally difficult (Parkes and Ungar 2003).

A review of the types of learning mechanisms used in evolutionary economics is beyond the scope of this thesis. As such, this section will highlight the importance of learning for evolutionary economics and MAS. Learning and other adaptation strategies necessarily constitute *feedback* mechanisms that facilitate movement towards steady-states in dynamical economic systems in the absence of assumptions about rationality and perfect information. In classic analytical economics, equilibria are founded upon

such assumptions in the face of *strategic interdependence*⁷. Evolutionary economics on the other hand assumes that the actions taken by one agent directly affect the decision set of all other agents *ad infinitum* (Parkers and Ungar 2003).

The importance of time and system evolution is highlighted when feedback is considered. In evolutionary models, feedback is assumed to occur as the model evolves, not once all agents have acted rationally. Because agents are assumed to be imperfectly informed, feedback is necessary for model evolution, in contrast to a situation where agents instantaneously achieving a mutual consistency (Friedman 1998, Richter 2004). More details regarding learning and feedback as assumed in this thesis will follow in subsequent chapters.

2.1.5 Complexity and Emergence⁸

The study of economics has historically focused on studying equilibria, and typically these are static patterns that do not account for temporal or behavioural adjustments. This type of analysis requires making simplifying assumptions in order to arrive at analytical solutions. However, incorporating feedback and learning into economic problems has been shown to modify strategic behaviour that had otherwise been assumed fixed or was simply ignored in classical models. To this end, static patterns may not be sufficient for explaining strategic behaviour in the face of learning and information feedback (Arthur 1999).

Some economists have begun studying how relaxing assumptions within general equilibrium, game theoretic, and rational expectations models might affect the individual actions, strategies and expectations as well as the aggregate patterns these create. The result, *complexity economics*, is not considered an accessory to traditional economic theory, but a general *out-of-equilibrium* theory (Arthur 1999).

⁷ This occurs in systems where the actions of one agent may affect the utilities of other agents.

⁸ It is beyond the scope of this thesis to discuss the mathematics of complexity in detail. As such, this section will provide the reader with the basic intuition necessary to understand the fundamental elements of complexity. The interested reader should see Day (1994) for a more detailed description of the mathematics of complexity.

Complexity economics requires the characterization of a system in a non-reductionist manner (Manson 2001). Simply put, a system must be more than the sum of its individual components. The “complexity outlook” requires that we emphasize the *formation* of structures rather than their given *existence*. When this is done, economic problems can be modeled differently. For example, rational expectations assumptions can be valid, but they imply that agents deduce what theoretical model will work and that all agents know that all other agents know what model will work (Arthur 1999). Assuming that such a knowledge structure exists may be unrealistic.

Complexity economics considers the evolution of systems as opposed to a focus on the steady state⁹. Economics has generally been studied under the lens of general systems theory - whereby systems are typically studied as static entities linked by linear relationships defined by stocks and flows of information, energy, or matter. Systems theory says nothing about the quality of the stocks or flows. On the other hand, complex systems are characterized by non-linear flows of constantly changing entities. Using complex systems analysis means it is possible to examine the qualitative attributes of the flows, such as learning and communications (Parker et al. 2003).

One important characteristic of complex systems is the inherent non-linearity of the way features of the system move together. As a result, inferences about complex systems must be derived in a manner that differs from classical models in which the variables in the system are mostly linear. In addition, complex systems are often characterized by feedback effects that generate non-linearities, even when individual behavioural rules are simple in structure (Durlauf 1997). To that extent, even simple assumptions about learning can lead to models that are complex in nature and impossible to solve analytically (Parker et al. 2003).

A final point is that history matters in complex systems. Intuitively, this means that long-run outcomes are influenced by short-run behaviours – a condition also referred to as “path dependence”. Path dependence implies that particular events in a system have

⁹ Note here that “steady state” does not refer to equilibrium but rather that the behavioural characteristics embedded in the system are dynamically evolving in a certain fashion (Durlauf 1997).

long-run consequences or that particular events (shocks) are not completely self-correcting (Durlauf 1997).

From this discussion about complexity emerges the following question: What results can we expect from the modelling of economically complex systems? The answer to this question is both exciting and daunting. Expect the unexpected. Durlauf (1997) states: “a system is said to be complex when it exhibits some type of order as a result of interactions of many heterogeneous objects.” Order in the complexity is often referred to as “emergence” or “emergent behaviour” and a process is generally considered to be emergent if “interactions occur at a level of description other than that at which the patterns occur” (Durlauf 1997). Alternatively defined, for an incident to be deemed emergent it should be unpredictable from a “lower level” (i.e. the summation of the elements of the system). Regardless the definition, it is important that the emergent phenomenon be irreducible to the basic elements which formed it.

In MAS, emergence occurs when agents interacting in a system behave in ways that could not have been foreseen *a priori*. One of the first such examples in the social sciences literature is the work of Schelling (1971). Although Schelling did not use computational MAS, his work has been reproduced in several MAS settings. Schelling showed that a small preference (behavioural rule) for one’s neighbours to be of the same ethnicity can lead to total segregation of the population, which was an unexpected result. To this end, Schelling concluded that when individual agents behave according to a simple rule, the collective behaviour of the system can produce a drastically different, more complicated behaviour – self-organization.

Complexity and emergence are clearly important concepts for consideration in economics when one considers issues of multiple-equilibria, non-predictability, inefficiency, historical path dependence, and asymmetry (Arthur 1999). Over time, the culmination of random events and positive feedbacks result in dynamic, non-linear processes that cannot be adequately described in a static environment (Arthur 1999).

2.1.6 Challenges with MAS

As a modelling tool, the use of MAS raises issues that need to be highlighted. To start, several researchers note that modeling learning using MAS, as well as the results obtained from simulating learning, must be interpreted with caution. This is the case particularly because many of the learning mechanisms employed in MAS are simply optimization strategies modified to suit an MAS framework. In effect, the use of such strategies may lead to results similar to neoclassical economics, negating some of the benefits of using MAS. In light of this, it is vital that research continues into the choice of learning mechanisms and how such decisions will affect results obtained in a simulation (Tsfatsion 2002).

Another issue with MAS is the use of behavioural rules. Autonomous agents within an MAS act/react to their environment through a series of behavioural rules bestowed upon them at the beginning of the simulation. Therefore, agents' decision strategies are limited by the set of behavioural rules in which they are contained. It is particularly important that behavioural rules reflect, as closely as possible, the behaviour of human subjects making the same decisions.

Some MAS models can also be sensitive to initial parameter settings (Gilbert et al. 1999). Although MAS is designed to limit the influence of path dependence by allowing emergent behaviour, some systems can be seriously affected by the initial parameter values chosen. Such problems can be overcome by running several tests with alternate initial parameter settings and testing the significance of such parameters on the results. In fact, all of the major issues with MAS can be mitigated with careful planning and consideration of causalities before any conclusions are drawn.

Finally, Parker et al. (2003) highlight some more philosophical issues with MAS. They note that some have criticized MAS as not being a valid way of doing science since it does not fall into the deduction/induction framework and results cannot be proven in a mathematical sense. They also note that there are still limits to understanding complexity and that the science of both complexity and MAS are still in their infancy.

While these issues are interesting and worthy of further exploration they are beyond the scope of this thesis.

2.2 Farmland Markets

This section will review applicable literature pertaining to farmland markets. Specific attention will be paid to the uniqueness of farmland and how it differs from other goods that are sold through auctions. There will also be a review of the literature that deals specifically with theories about farmland auction mechanisms and bidding schemes.

The literature on farmland markets is rich and deals mostly with the influences of production characteristics that affect farm income, government payments, capital gains (e.g., Shi, Phipps, and Colyer, 1997; Alston, 1986). It should be noted here that the purpose of this thesis is not to develop alternative methods of price formation in farmland markets; this topic has been thoroughly discussed (see King and Sinden, 1994 for a review). Rather, the focus of this thesis will be to determine the effects of auction choice on price level, auction efficiency, and industry evolution.

2.2.1 “Flowers versus Farmland”: Why is farmland so special?

Auctions have traditionally been used to sell a variety of goods. Most famously perhaps have been the recent flurry of US radio spectrum licences and off-shore oil licences, as part of the deregulation of network industries all around the world. When Vickrey (1961) developed the Revenue Equivalence Theorem (RET) for auctions he did so under the assumption of independent private values, a phenomenon that may not always be applicable with goods to be auctioned. Nevertheless, many auctions are still designed with independent private values¹⁰ in mind.

Farmland is one good that does not fit into the independent private values model. Firstly, farmland is a capital asset that can be resold in the future. It is long-lived and generates income over that time; it is also spatial in nature and cannot be transported. For these reasons, time and space matter when pricing land. There is speculation about

¹⁰ Under independent private values, goods to be sold have a definite subjective value to each bidder that is known with certainty by that bidder.

the price of land, and the revenues it will generate long into the future. Land is also scarce, especially in a spatial fashion – there are only so many acres available in a given radius surrounding any particular location¹¹. It is the combination of these qualities that make farmland unlike fine art or flowers; and a one-shot independent private values model of farmland auction markets may not function as expected.

One of the most important features of farmland however, is its affiliated-values characteristics (a full description private-, common-, and affiliated-values will follow in later sections). Affiliated values in our context means any given agent's valuation for a plot of farmland is a function of their private-value, plus a common-value that is observed from other auctions and bidding behaviour. Incorporating the notion of affiliated-values greatly complicates the theoretical auction literature, as will be seen in later sections, since noisy common-value observations cause uncertainty and decrease efficiency (Goeree and Offerman 2002).

Because of farmland's unique characteristics, designing an optimal auction mechanism for it is likely to be a daunting task. Instead, this thesis will attempt to incorporate the characteristics that are unique to farmland and we use simulations to draw conclusions about the comparative utility of various auction mechanisms.

2.2.2 Models of Farmland Auction Markets

There have been few attempts to model farmland auction markets. One of the best known was by Colwell and Yavas (1994). They developed a model of strategic bidding in farmland markets when auctions are two-staged. In the first stage, land is divided into equal tracts and auctioned off independently. The second stage involves auctioning off the entire plot of land as one piece¹². The authors assume independent private values and arrive at a subgame perfect Nash equilibrium strategy assuming agents behave non-cooperatively, meaning there are no collective bidding agreements. A

¹¹ Although fine art (e.g. a Picasso) can also be considered scarce, scarcity in farmland markets arises from spatial scarcity – because it may not be profitable to farm land 200 kilometers away.

¹² This two stage game resembles a combinatorical auction, a topic that will not be considered in this thesis. Combinatorial auctions are known for generating bidding strategies that are complex and very difficult to solve. This thesis will examine repeated 1 stage games in an attempt to shed light on auction design issues, not optimal bidding strategies.

subgame Nash equilibrium strategy is used because land is auctioned off in multiple stages and a solution concept requires that an equilibrium must be found in stages of the game, not the extended game itself.

Given that information in their model is perfect and private-values is assumed, players in the Colwell and Yavas auction are capable of formulating best response strategies based on their information, and the known best responses of other agents. A subgame perfect Nash equilibrium exists when an agent's strategy leads to an optimal outcome for every agent in the game based on a given strategy for all other players at each node of the extensive form game. This type of game is solved using backwards induction and relies on perfect information and finite number of possible strategies, or moves, for each player.

Although interesting, this work makes assumptions about bidder private-values in order to arrive at a computable equilibrium strategy. As noted above, it is believed that farmland does not display the elements of the private-values assumption. As such, the results generated in Colwell and Yavas (1994) would seem to have limited value in the real world.

There is another distinct thread of literature that attempts to explain price dynamics in farmland, but none of these deals specifically with the structure and dynamics of auction markets. Furthermore, there are no known papers that employ MAS to examine farmland markets. Freeman (2005) and Balmann (1997) use an auction-like mechanism in their research, but it is extremely simple and it is worth noting that the auction market is not the main focus of their work.

2.2.3 The Next Step in Farmland Auction Market Design

This section outlined the features of farmland that make it different from traditional private-values goods in effect motivating the need for a non-traditional approach to the study of auctions. The literature on farmland auctions has not addressed the issue of affiliated-values adequately. I endeavour to enrich the literature to include evolutionary economics principles to the study of farmland auction markets in order to develop a

more complete understanding of the effect that farmland characteristics have on prices, variance, and efficiency when land is sold via auction.

2.3 Mechanism Design: Auctions

Mechanism design is a subfield of economic game theory. Its goal is to design rules of an asymmetric information game so as to elicit a desired response from players, generating the desired (most efficient) outcome. One of the most frequently studied branches of mechanism design by economists is auction theory. Proper mechanism design relies heavily on the solution concept chosen to arrive at the desired result. Economists have traditionally used Nash solution concepts when designing auction mechanisms. This section will examine the role that Nash solution concepts have played in sculpting current auction theory. It is important to note that there is a well understood sense of what can and cannot be achieved with mechanism design of auctions using Nash solution concepts because of the strong assumptions it makes about agents' information and beliefs about other agents (Parkes and Ungar 2003). The limits to a Nash solution should be apparent after reading this section.

2.3.1 Roots of Classical Auction Theory

This section will serve as an introduction to basic auction theory: where it originated, some of the assumptions underlying it, and the importance of risk preference and valuations. A discussion regarding optimal auctions and efficiency will highlight some of the advantages and drawbacks of examining auctions through a game theoretic lens. Finally, a review of literature on mechanism design enrichment and feedback and learning in experimental economics highlights some of the issues relevant to traditional Nash solution concepts.

2.3.1.1 William Vickrey and the Revenue Equivalence Theorem

The Revenue Equivalence Theorem that has been so widely celebrated in economic literature for a half a century was first formulated by Vickrey (1961) and later generalized by Myerson (1981). Vickrey showed that, given the following assumptions, certain auctions will yield the same expected seller revenue and allocation of goods.

- Highest bidder wins the auction and receives the good
- Bidders have independent private values and drawn from the same, commonly known distribution - values and bids are IID
- Bidders are risk neutral
- Bidders are not budget constrained
- Bidders are perfectly rational and know that all other bidders are also perfectly rational, *ad infinitum*.

The Revenue Equivalence theorem was developed under rather strong assumptions - risk neutrality, IID, perfect information, and homogeneity - in order to ensure that players could find a Nash Equilibrium bidding solution. This last point is particularly important to this thesis because auction theory has traditionally been examined using Nash Equilibrium bidding functions (Richter 2004).

Vickrey's work showed that under the assumptions listed above, all private-valued auctions, including the well known English, Dutch, FPSB, or SPSB auctions yield the same expected seller revenue and allocation of goods. It was this single piece of work that gave birth to modern auction theory.

2.3.1.2 Risk Preferences

Risk preference for buyers (and sellers) in auctions is a topic of importance to this thesis. It is now commonly known that any degree of risk aversion invalidates Revenue Equivalence and results in first-price auctions (Dutch) to be more profitable than second-price auctions (English) (Smith and Levin 1996)¹³. Intuitively, this would suggest bidders prefer second-price auctions relative to first-price, but in fact such a result does not always hold. For example, Matthews (1987) showed that if bidders exhibit decreasing absolute risk-aversion (DARA), a second-price auction is preferred, while the opposite is true if bidders have increasing absolute risk aversion (IARA). There are currently a number of papers examining alternative risk preference schedules under alternative auction mechanisms - for further reading see Maskin and Riley (1984). However, the literature tells us nothing about heterogeneous agents, either buyers or sellers, whose risk preferences can change over time.

¹³ In much of the literature it is commonly assumed that sellers are risk neutral.

2.3.1.3 Private, Common, and Affiliated Values

Another of Vickrey's original assumptions about auctions that is often the topic of extensionary research is the independent private-values assumption (IID). Originally, Vickrey assumed that bidders would value a good independently of how other bidders valued the same good. Clearly, this assumption however does not apply to all goods that are sold by auction. In light of this, Wilson (1969) suggested what is known as the common values approach. Common-value means that all bidders value a good equally, but its actual value is unknown to all agents. Individual values are therefore based on each agent's best private information about the good. In effect, these values can differ between agents, but they are solely a function of the information available to each agent. The common values assumption is best known for generating the so-called *winner's curse* situation: in common-value auctions with imperfect information, the winner tends to over pay for the good since the actual value of the good is likely to be closer to the average of all values.

There is a third type of values model that is commonly modeled in auction theory. It uses elements of both private and common values to generate bidder valuations. Milgrom and Weber (1982) proposed a model of competitive bidding that accounts for personal preferences, preferences of others, and the intrinsic qualities of the good bid on. They developed what is called the *affiliated-values* model. Affiliated-values depend directly on the private information of all bidders; high valuation by one bidder makes high valuations by other bidders more likely. Their model yields higher prices in an English auction than a second-price auction, a result that contradicts standard private-value auction theory. It should be noted that the majority of analytic auction theory relies on the private-values assumption because common- and affiliated-values models significantly increase the algorithmic complexity of the problem because of the need to incorporate these interdependencies (Matthews 1987). As such, little is understood about the effects of using common- and affiliated-values assumptions for bidding agents.

2.3.2 Optimal Auction Design

The literature on optimal auctions is vast and continually evolving. As such, it is impossible to discuss all avenues of research in this thesis. Alternatively, this section will comment on the literature in general and highlight a select few papers that relate to important issues not raised in this thesis.

Since Vickrey (1961), much of the work on optimal auctions (and auctions in general) has focused on maximizing revenue for the seller given either; 1) the classical IID assumptions laid out by Vickrey and alternative types of auctions, or 2) abstractions from the IID assumptions.

Riley and Samuelson (1981) highlight optimal auction conditions under IID assumptions and discuss the implications of relaxing these assumptions. Unfortunately, they address only a small subset of all possibilities. And Klemperer (2002) discusses some of the institutional issues associated with optimal auction design, such as entry and collusion. By using the lens of antitrust theory, he is able to comment on the likely success of different types of auction in the face of practical “auction failures” such as too few bidders or high information costs. Klemperer contends that what is important in auction design is not a one-size fits all auction, but rather a particular auction’s robustness against these factors and its attractiveness to potential bidders. That is to say, “in practical auction design, local circumstances matter, the devil is in the details” (Klemperer 2002).

Alternatively, in spite of the overwhelming trend to study optimality on behalf of the seller, i.e. revenue equivalence, a few papers addressing the bidder have emerged. One such paper is by Matthews (1987), where he compares bidders’ preferences for different auctions dependent on their risk preference and the assumption that values are independent and private. He suggests that in order to examine auctions that are optimal for the buyers, it may be useful to examine revelation mechanisms that maximize the weighted sum of *ex ante* utilities subject to: *i*) a constraint binding expected utility from below; *ii*) interim participation constraints requiring the buyers to be willing to participate once they know their types; and *iii*) incentive constraints requiring that

truth-telling be a Bayesian-Nash equilibrium. Matthews also notes that in the face of private-, and in some cases affiliated-values, little can be said if bidders are risk averse without making strong assumptions.

The literature on optimal auctions is extensive and encompasses a variety of cases based on the original framework put forth by Vickrey. Nevertheless, very little of this research comments on the applicability of such schemes in the real world and only recently has work on learning and the evolution of repeated auctions begun to appear in the literature. As such, there is much work to be done if theory is to give practitioners insight into real life auction design.

2.3.3 Auction Efficiency

Along with auction optimality (maximizing seller revenue or buyer utility), the notion of auction efficiency is used as a means by which to rank alternative auctions.

However, unlike the case of auction optimality, there is a more general consensus about the meaning of efficiency. For the purposes of this research, efficiency will be defined as in Maskin (2001). Assuming no ties for the highest valuation, and if bidder i is the winner, an auction is considered efficient if:

$$V_i(S_1 \dots S_n) \geq \underset{\forall i \neq j}{\text{Max}_j} [V_j(S_1 \dots S_n)] \quad (2.1)$$

Thus an auction is efficient if the winner of the auction is the bidder with the highest valuation, conditional on all available information – all buyers' signals. This type of efficiency is referred to as *ex post* efficiency and it assumes that the social value of the good is equal to the maximum of the potential buyers' valuations. This definition of efficiency is chosen because it is the one that is most often used when evaluating actual auctions, like the well-publicized auctions for spectrum licenses and electricity capacity. In these types of auctions, the good being purchased is used to produce a good that is subsequently sold in a market without significant externalities. In this light, a definition of efficiency for auctions that sell spectrum licenses could well map on to the definition of efficiency for auctions that sell agricultural land as an input for producing agricultural commodities.

It is well established that sufficiently many buyers and values guarantee that the Vickrey auction is efficient. However, the efficiency criterion fails when the private values assumption does not hold. In this regard, Dasgupta and Maskin (2000) proposed a new type of auction that maintains efficiency in the face of common-values. Their research shows that a generalized Vickrey (second-price) auction can be fully efficient, even with multiple goods and common-values, provided that the signals between players are one-dimensional. They also show that if signals are multi-dimensional, full efficiency is unattainable by any type of auction. This result is particularly important because it demonstrates that, with the current theoretical tools, it will not be possible to solve more complex common- and affiliated-value auction problems. Their result raises a serious question since many real life auctions do not meet the private-values assumption. Once again, it appears that there is a need to develop new avenues for studying more complex applied auction problems.

2.3.4 Experimental Auctions

2.3.4.1 Enrichment of Mechanism Design

Enriched models attempt to use existing theories to make complicated extant auction frameworks applicable to everyday use. Many academics contend that current “optimal” auction frameworks are too difficult for bidders to use efficiently. Milgrom and Weber (1982) suggest that in order for the practical literature to catch up with the theoretical, more emphasis must be placed on realistic auction designs that make bidding and selling strategies more user-friendly. Rothkopf and Harstad (1994) offer a similar message. The theme of the latter work is that increasing the realism of existing auction models yields a tendency to change the results of theoretical predictions. They suggest there is a gap in the literature as a source of directly applicable models and that better modeling improvements would be more useful than additional equilibrium concepts under hypothetical situations.

2.3.4.2 Bid Feedback and Learning in Experimental Economics

There is a growing literature in bidding theory that uses experimental economics to compare individual bidding behaviour against the risk-neutral Nash equilibrium model (RNNE) proposed by Vickrey (1961). However, much of the empirical evidence suggests that winning bidders in experimental auctions are significantly overbidding relative to what RNNE assumptions would predict (for a review, see Kagel 1995). In response to this, the constant relative risk aversion model (CRRAM) was developed by Cox et al. (1988). This model generalizes Vickrey's original work and allows for a degree of heterogeneity of bidders. The CRRAM model did not solve the problem; it merely opened up a discussion concerning CRRAM's ability to adequately explain overbidding.

In response to the debate over CRRAM, an alternative bidding theory has recently been developed. It is called Impulse Balance Theory and Learning Direction Theory (LDT) (see Selten (2004) for an overview) and is an attempt to explain systematic overbidding by individuals in experiments. Neugebauer and Selten (2006) have also developed an experimental individual choice framework under which to test RNNE, CRRAM, impulse balance theory, and LDT.

LDT is based on the concept of bounded rationality. After a subject experiences a loss, LDT assumes that the subject tends to increase his bid in hopes of producing the winning (highest) bid in subsequent auctions. Following a successful (winning) bid, the theory postulates that the subject would tend to decrease his bid in order to capture the entire surplus available in subsequent auctions while still winning the auction. On the other hand, impulse balance theory (Selten 2004) permits quantitative predictions of the long-run effects of LDT. Impulse balance theory applies to those economic situations in which clear activity impulses exist. Simply put, the theory hypothesizes that impulses involving greater gains are relatively more important to individuals. Impulse balance theory also suggests the existence of an impulse balance point at which upward and downward impulses cancel out in the long run.

Using this framework, Neugebauer and Selten (2006) find that the general one-shot Nash equilibrium game assumed in most auction models does not apply in a repeated game setting and they offer that information feedback leads to the overbidding behaviour that is often observed in experimental auction games. More specifically, they find that individuals with different *ex post* information bid differently in subsequent games and that those who have been given clear impulses or signals offered bids that were closer to the impulse balance point than either RNNE or CRRAM in over 50% of the cases.

2.4 Multi-Agent Simulations of Auction Markets

Using MAS to explore auctions is not a new avenue of research; in fact, there are a number of papers that have used MAS to examine the effects of learning, heterogeneity, or affiliated-values on classical revenue equivalence theories. Much of this literature has been fuelled by the realization that bidders cannot, in almost all cases, bid homogeneously according to their Nash bidding strategies (Richter 2004).

There is a growing literature on auctions conducted with artificially intelligent agents. The following sections will highlight the benefit of using MAS for research into auction theory based on a selected few of these papers.

2.4.1 Benefits to Using MAS for Auction Simulation

The following sections will highlight some of the advantages to using MAS for auction simulation. It will begin with a discussion about evolution and “steady-states”. Next, asymmetries in auctions will be considered, and this is followed by a description of the *out-guess-regress* problem, and finally, learning in auctions. In all cases, this section points out the advantages of using MAS in place of analytic game theory to examine auction mechanism design. The issues discussed below are of great importance to mechanism design, but at the present, game theory is unable to model them appropriately (Parkes and Ungar 2003).

2.4.1.1 System Evolution and “Steady States”

I have already described one of the major advantages of using MAS for auction analysis. Equilibria in MAS do not simply *occur*, but in fact, they are evolved (if they are achievable at all). Friedman (1998), Parkes and Ungar (2003), and Richter (2004) all speculate that assuming Nash behaviour overlooks the reality that in real world auctions, repeated playing is required if any sort of efficient equilibrium is ever to be reached.

Richter (2004) tested the results of the revenue equivalence theorem (RET) with static auctions against results from evolutionary agent auctions. Results indicated that when agents are unable to instantaneously, and simultaneously behave Nash-like, RET fails for a variety of auction mechanisms.

Evolutionary economics seeks to understand if and how *a priori* heterogeneous bidders arrive at Nash equilibria. By simulating evolutionary games, researchers are able to observe if and how such equilibria are achieved, and in their absence, if a “stable steady-state” of the system evolves. By definition, a steady-state in this sense “... is stable if, loosely, all nearby trajectories go to it.”¹⁴

The primary difference to note between evolutionary steady-states and standard equilibria is the element of time. In most cases, equilibria are assumed to happen instantaneously, and remain so until an element of the system changes, at which point a new equilibrium is found. Steady-states incorporate the element of time, and evolve with the system. Complex systems can be in or out of a steady-state. Systems that start in a steady-state will remain so certain factors are changed, at which point, the system evolves again over time until a new steady-state is reached (if at all). Complex systems that begin out of steady-state will attempt to evolve over time towards a steady-state, if one exists. Some complex systems contain no steady-state, and these systems can cycle back and forth with constant or increasing intensity.

¹⁴ Definition taken from: <http://economics.about.com/od/economicsglossary/g/stabless.htm>

It is important to understand that the term steady-state in the evolutionary or complex sense does not imply static behaviour; a steady-state as referred to in this thesis implies an out-of-equilibrium system (i.e. the system does not assume instantaneous equilibrium) that demonstrates a converging trend or displays patterns of consistency (Arthur 2005). The very nature of MAS lends itself to out-of-equilibrium analysis where systems are analyzed to uncover the existence of steady-state characteristics.

2.4.1.2 Information Asymmetries

Game theoretic models necessarily make assumptions about the commonality of individual knowledge to ensure that equilibrium is reached. Namely, either the preferences and rationality of agents of all agents must be common knowledge, or the agents must know each other's choices. These assumptions are often impractical since it is often the existence of private and asymmetric information that motivates market decentralization (Parkes and Ungar 2003).

MAS systems are capable of dealing with asymmetries in information by assuming either; 1) the system has a dominant best-strategy for all agents in the game (i.e. bidding in a Second-Price Auction); or 2) the play of repeated games where agents learn and adapt to the asymmetries and try to move towards a steady-state (Parkes and Ungar 2003). Attempts to model information asymmetries under a classical game theoretic lens either require unrealistic assumptions, or result in a complex problem that is unsolvable analytically. The issue of asymmetries of information brings us back to evolutionary game concepts and evolving systems of autonomous, interacting economic agents.

2.4.1.3 The “*Out-Guess-Regress*” Problem and Bounded Rationality

Economic theory offers little insight about how to model behavioural norms, such as learning and the speed of the learning process, both of which are known to be present in almost all real auction markets. In fact, game theory tends to abstract from such difficulties due to the complexity that they bring to the analysis. Theoretical results about behavioural norms are limited to very simple models and are still incomplete

(Zeng et al. 1998). In fact, even simple models of learning become complex and analytically impractical very quickly (Tsfatsion 2002). But a properly designed MAS enables researchers to examine the effects of behavioural norms in repeated auctions and observe the negotiation process in real time. Others offer that MAS allows a focus on formulating protocols to emulate the negotiation process and also mimics sequential decision making techniques used in actual auctions (Zeng et al. 1998).

Currently, game theoretic models developed with assumptions about highly rational agents cannot properly model the negotiation process when strategic interactions and learning are incorporated. Incorporating such assumptions into game theoretic models results in a problem called *outguess regress*, whereby individual agents anticipate the movements of others, knowing that others are anticipating these movements, knowing that other agents know about anticipating movements, and so on. Assuming bounded rationality (i.e. an agent with incomplete information or capabilities for solving a desired problem) in MAS eliminates one part of the “strategic” element and replaces it with uncertainty and beliefs about other players, thus leading to system convergence in a finite number of steps. This view is supported by Selten (2001), who argues that while rational choice models can have considerable explanatory power, some of the axiomatic assumptions of rational choice are contradicted by experimental evidence and may not translate to individual behaviour. In addition, Parker et al (2003) believe that a boundedly rational behaviour set that represents goal oriented decision making should be preferred to an optimization strategy resulting from fully rational agents.

Despite the limitations of game theoretic models for accommodating behavioural norms, they are still useful for developing a foundation upon which MAS of auctions can be constructed. In this thesis, game theory will aid in forming the general outline of the auction markets and agent behaviour.

2.4.1.4 Learning in Auctions

MAS learning has been a topic of increased exploration since researchers have realized that rational behaviour and optimization were not a complete and robust algorithm for generating simulated behaviour that mimics real world behaviour (Tsfatsion 2002).

Research on learning in artificial intelligence (AI) and MAS simulations began by endowing agents with genetic algorithms¹⁵ (GE) as learning mechanisms. However, many GE's in this sense were originally developed with assumed optimality conditions in mind, and as a result, they sometimes fail to capture the salient features of decision making processes in a social setting (Teshatsion 2002).

In order to more accurately reflect real economic learning processes, a number of suggestions have been made about how to model learning mechanisms. Gintis (2000) suggests “departing from the traditional view of game theory as a formal study of rational behaviour among strategically interacting agents”. Rather he promotes an “embodied mind” approach, whereby games are strategic interaction problems rooted in natural and social processes. He offers that economic agents repeatedly wrestle with a series of problems over time and slowly evolve the ability to play games successfully.

Wei (1995) believes that MAS learning is possible only when several agents are present. To that extent, economic learning more closely resembles learning from the existence of societal structures surrounding agents. In fact, there are numerous classes and categories of learning mechanisms used in MAS. Learning mechanisms are often grouped under one of two general headings; (1) logic based learning, and (2) biology based learning (Alonso et al. 2001). While a complete overview of suggested learning mechanisms in MAS is beyond the scope of this thesis, several important examples of learning mechanisms need to be discussed.

Zeng et al. (1998) developed a Bayesian method of learning in MAS where agents update their prior beliefs (distributions) based on newly acquired information. Their model investigates a competitive bidding negotiation process where agents are self-interested and update their perception of other agents based on bids and counter offers in the negotiation process. Their results show that efficiency, speed and joint utility increased with learning relative to no learning in a sequential negotiation model. This finding certainly suggests that learning can be applied to MAS simulation and that

¹⁵ A genetic algorithm is a technique used to find exact or approximate solutions to search or optimization problems. For more information on GE's see: Goldberg, D. E. (1989) *Genetic Algorithms in Search, Optimization and Machine Learning*, Kluwer Academic Publishers, Boston, MA.

simple forms of learning - updating beliefs - can greatly improve the efficiency of economic interactions.

I suggest the effects of learning in MAS have a far greater impact on the system than is initially apparent. One of the side effects of learning agents is the manner in which they affect each other. Consider the case of a Bayesian learning environment, as discussed above, with several agents. Actions taken by the first agent will force all other agents to update their beliefs about this agent. However, since every agent knows that every other agent is updating their beliefs, all agents must update their beliefs about all other agents. Consequently, all subsequent actions taken by other agents will be affected by the actions of the first agent because this action altered the beliefs (and subsequent actions) of all other agents. This type of reasoning can be applied to every action that every agent takes, meaning that the actions of all agents are affected by the actions of all other agents. This is a classic example of dynamic feedback.

While the Bayesian learning approach may be considered a ‘direct’ information feedback mechanism because feedback comes from other agents, such mechanisms need not be direct to have observable consequences on the evolution of a repeated game. Hailu and Schilizzi (2004) provide a prime example of such a result. They develop a simulation model of agent bidding where agents learn based only on the consequences of their own actions. That is, agent’s bids in time $t + 1$ are affected only by their bid in t and whether or not they won the auction. In this case, agents are not updating their beliefs about other agents, or using bidding information provided by other agents to adjust their bids. In their model, agents adjust their bids based on the following simple rule, with probabilities p and $1 - p$ respectively: (1) if the previous auction was won, the agent bids the same or increases her bid by 10%; or (2) if the previous auction was lost, the agent bids the same or decreases her bid by 10%. Clearly, agents change their bids based only on their previous bids and the state of the outcome of the auction in the previous round. Yet despite its simplicity, this learning scheme results in indirect feedback that affects the behaviour of all agents and the evolution of the game.

At the heart of an MAS is the autonomy of individual agents, and it is this autonomy that permits agents to act – at least in part - on the actions of others in the system. This notion is quite different from the majority of traditional economic models in which agents interact only via market clearing prices (Durlauf 1997). Such direct interactions in turn allow economic MAS models to capture far more behavioural norms than their traditional counterparts. It is these interactions between agents that generate called feedback. In turn, systems containing feedback can exhibit multiple types of self-directed behaviour on an aggregate level. In other words, feedback permits agents in a population to learn and make *similar types of decisions*, without knowing exactly what decision will be made or imposing constraints on the set of decisions to be made (Durlauf 1997). Making similar choices and conformity as a result of feedback from learning is another potential source of emergent phenomena in complex systems.

2.5 Summary

This chapter has laid the groundwork for the model that will be developed in this thesis. I have also motivated the use of MAS for studying the complexities of farmland auction markets. The simulation model that follows is developed using ideas from MAS, game theory, and farmland markets and as such calls on diverse threads of literature to capture all of the salient features observed in real world farmland markets.

CHAPTER 3

CONCEPTUAL MODEL

3.0 Introduction

This chapter outlines the conceptual model that underlies this multi-agent simulation. It begins by rhetorically describing the model and the assumptions that govern its function. The agents (players) are described, followed by a description of the behavioural and structural equations that make up the simulation model.

This simulation is comprised of a series of relatively simple behavioural equations for each agent, and each agent makes calculated decisions based on experiences and expectations that affect the decision set of all other agents in every time period to come. The informational asymmetries, agent heterogeneity, feedback, and the importance of time and space create a complex economic environment that benefits from the use of MAS as a tool for analysis.

3.1 Model Flow

This section illustrates the general flow of the simulation model of farmland auctions. Understanding the flow of the simulation will greatly aid in understanding how, when, and why agents make certain decisions. Later sections will describe in more detail the agents in the model (farmers and retirees) and the assumptions guiding their behaviour.

Figure 3.1 is a flow diagram outlining the major steps taken by agents in the simulation. Farmers start at time $t = 0$ in the *Crop Production Module*, where all production, harvesting, and crop sale activities take place. Farm agents then move on to the *Farm Finances Module* where agents determine if they should remain in the market or exit. Exit can occur for a variety of reasons discussed in more detail below. Farmers who exit the industry become retirees and move to the Auction Module, where they remain

until all their land is sold, at which point they exit the simulation completely. Farm agents who decide to continue farming will then enter the *Expectations Module* where they update their expectations about future crop prices and yields. They subsequently attempt to purchase land if they are financially able. Otherwise, they do not purchase land and wait until the next growing season. All farmers remaining in the simulation receive farmland price information from auctions via an information diffusion mechanism. This diffused information becomes the learned price information upon which individual bids are based.

Finally, farm agents who meet the necessary criteria enter the *Auction Module* and bid on plots of land as they become available until they have purchased all the land that they require, at which point they exit and wait until either; 1) all land is sold, or; 2) there are no bidders remaining. Subsequently, all remaining farmers proceed to the *Crop Production Module* and another simulated year begins. Additional detail about each module is provided in subsequent sections.

3.1.1 Farmers

Farmers are the first breed or type of agents in the model. Farm agents are assumed to produce crops on their land and sell them at market prices. All farmers aged < 55 are assumed to want to expand their farm size by purchasing land from farmers who are exiting the market.

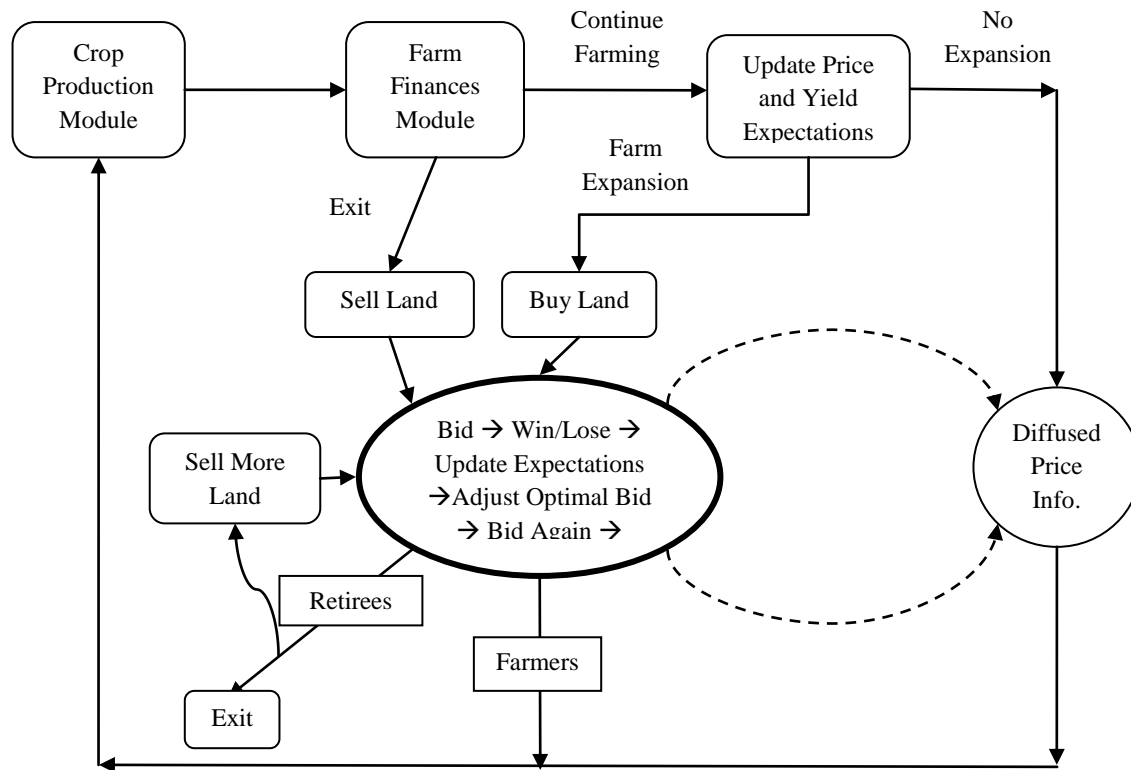
In contrast to some other related work on farmland markets, this model assumes no leased land or leasing market. This assumption is made so that emphasis can be put on the market for buying and selling land, as is typically the case in North America and the region under analysis¹⁶. Farmers in the simulation are initially endowed with land, machinery and cash. I also assume that there is no government support for farmers and no off-farm income. Income is generated based solely on a farmer's ability to farm the land successfully¹⁷. Farmers seek to invest positive income streams by purchasing land

¹⁶ This is in contrast to European markets where most farmland is leased by producers.

¹⁷ It is important to note that the author has considered the implications of making these assumptions. They are made in order to focus the analysis on the issue at hand – farmland auction markets. Without leasing, farmers are forced to pay larger lump sums of cash if operations are to be increased. It also

at the lowest price possible, farming it until they exit, and then selling their land at the highest price possible through specified auction markets.

Figure 3.1 Simulation Flow Diagram



Farm agents farm all the land they own in each period until they are either forced out of the market for credit reasons, equity protection, or old age. In the simulation, a random percentage of farmers pass down their land to an heir if the farm is financially viable. Furthermore, farm agents are assumed to be rational and act upon the best information (albeit incomplete and asymmetric) available to them.

3.1.2 Retirees

Retirees are the second breed of agents in this model. Retirees are farmers who have left the industry and want to sell the land that they own. In this sense, once a farmer

implies that farmers take on long-term investment, as opposed to signing short term leases. The author is also aware that optimal farm scale and risk incentives are altered when government support and off-farm income are removed.

becomes retired they can be considered land owners who wish to sell their land once the right price arrives. If a retiree is unsuccessful in selling all her plots of land (due to a lack of local buyers or her reservation price not being met) in the first year of retirement, she is assumed to hold on to land that has not sold. Furthermore, it is assumed that she does not farm this land, nor does she lease the land¹⁸. All remaining plots of land go up for sale again in subsequent periods, but at a discounted price, and the agent further reduces her reservation price. This process continues each simulated year until all plots are sold. I also assume that farm agents pass on any unsold land to an heir when they die, and these agents in turn put the land up for sale. As such, there is no need to specify who actually holds the land once an agent retires, only that the land is for sale and the maximum price is desired by the owner. In other words, retirees have different incentives than farmers because they seek only to maximize cash sales of land. To this extent, it will be important that retirees set optimal reservation prices to extract the maximum amount of surplus from the buyer.

3.2 Commodity Production Factors

Farms are assumed to produce their crops using 3 inputs; land, labour, and capital. This section will highlight the importance of each of these inputs and how each input is characterized in the model. Much of this portion of the simulation is based on the work of Balmann (2000) and Freeman (2005).

3.2.1 Land

Each plot of farm land is assigned to 1 of 4225 plots on a 65 X 65 simulated grid that comprises the farming landscape. Each plot represents one quarter-section or 160 acres. In this model, plots are heterogeneous in cultivatable acres and quality. Cultivatable acres represent the number of acres that a farmer can use for growing crops, and this value is fixed throughout the simulation. For reference, the mean of cultivatable acres in the simulation is 150 with a natural upper bound of 160. Plot quality is also fixed and represents the soil quality of a specific plot of land. Quality is homogeneous within a

¹⁸ We understand that this assumption is unrealistic; however to reiterate, the assumption is made so that emphasis can be placed on the sales market.

plot, but varies across plots. In turn, each plot has a quality that is correlated to the plots surrounding it. Quality is tracked using a relational variable. Plots with higher quality (quality > 1) will have higher yields than plots with lower quality (quality < 1) *ceteris paribus*. Plots of average quality have quality normalized to unity.

Farmsteads are dispersed randomly across the landscape and physically situated on one plot. That plot is considered to be the farmstead plot until the farmer exits the industry and sells the plot containing the farmstead, at which time it is assumed that the new farmer of that plot utilizes it for cropping. Each plot can be owned by only one farmer at any time and all plots are assumed to be farmed in each period by their owner.

In each period plots are also randomly assigned a weather variable that affects yields in the same manner as quality. Weather is assumed to be diffused and, correlated across plots, in a similar manner as quality.

3.2.2 Labour and Capital

Similar to the work of Freeman (2005), I assume that farm agents supply most, but not all, of the required labour for crop production. Additional farm labour is purchased on the open market and family withdrawals are made to compensate farm agents for supplying labour. These issues will be discussed again in subsequent sections. For tractability, non-land capital costs are assumed to be in constant, fixed proportions relative to land usage.

3.3 Farm Agent Productivity

One of the key components of heterogeneity among farmers will be in their productivity measure - *Skill*. Farmers will inherently have different levels of productivity that I assume remain constant over time; productivity could be thought of as an exogenous variable like managerial ability. For our purposes, we will assume that farmers with higher skills are capable of altering crop mixes more effectively so as to extract more output than lesser skilled farmers¹⁹. Farmers of average 'skill' will have a

¹⁹ Allowing for information diffusion in the form of skill sets would be an extension to this thesis.

productivity level of unity. The distribution of skill level is chosen to be $\eta \sim (1, 0.05)$ with upper and lower bounds of 1.2 and 0.8 respectively.

Productivity is important for several reasons. Farmers who are more productive (*Skill* > 1) will produce greater yields, and thus more income, than farmers who are less productive (e.g. *Skill* < 1), *ceteris paribus*. Farm income is one of the key drivers in a farm's ability to purchase more land and grow. Also, by holding farmer productivity constant it will be possible to examine to what degree more productive farmers grow their land base faster than less productive farmers and if more skilled farmers have a higher success rate than less skilled farmers.

3.4 Entrepreneurial Attitude and Risk Preference

I assume that farmers are also heterogeneous in entrepreneurial attitude, and thus their risk preference. Farmers' risk preference, and therefore their willingness to assume risk, will be a function of their assumed goals and objectives for their farm enterprise. A life-cycle process, similar to that developed in Freeman (2005), is developed and will determine *the level of risk* that each farmer is willing to undertake. Farms in the simulation will operate in one of three phases: 1) Growth and Expansion, 2) Development, and 3) Maintenance. Phases are directly correlated to the age of the farmers. A fourth phase, Exit and Retirement, is also incorporated in the model and means that farmers who are close to retirement do not purchase any more land. However, this phase has no additional bearing on their risk preference.

During the Growth and Expansion phase, farmers will be mostly concerned with increasing farm size and subsequently will be willing to take on greater risk than a farmer in the Maintenance phase whose main objective should be equity protection (Olson 2004). Demographically, as farmers age they pass from the least risk averse phase to the most risk averse phase and finally on to the Exit and Retirement phase.

A risk neutral farmer (of which there are none in this model) would have a risk preference equal to unity. I also assume that all farmers within a prescribed age range

(Life Cycle Phase) have the same risk preference²⁰. Farmer risk preference is important in the land bidding process because farmers with higher risk avoidance preferences will tend to discount their maximum bid more than farmers with lower risk preferences. To this extent, risk preference and associated degree of bidding success can affect a farmer's ability to meet their goals and objectives. A farmer's risk avoidance preferences will also affect her risk aversion *for losing* an auction.

Farmers in this model are endowed with very simple goals and objectives. Primarily, all farmers desire to increase the number of plots owned throughout their lifecycle, until they reach the Exit and Retirement phase. One salient feature of this assumption is that farmers' utility is derived not by cash stocks, but by the number of plots managed. However, during the Exit and Retirement phase, it is assumed that farmers seek to maximize the revenue from selling their plots²¹.

3.5 Farm Agent Activities and Decision Parameters

Section 3.5 presents the equations that govern the actions of each agent throughout the simulation. Each sub-section will discuss equations that constitute the modules in figure 3.1. Given the discussion in the previous chapter, I aim to convince the reader that this economic system is complex. Many of the behavioural equations are very simple, but because of the bottom-up nature of the simulation, determining analytic solutions to this system, especially when agent interactions are considered, would likely be impossible.

3.5.1 Crop Production and Revenue

Farmer agents are assumed to generate gross crop revenue through the sale of their crops. All farmers are assumed to crop the same four types of crops, but in different mixes. As previously noted farmers with greater skill choose better crop mixtures and thus have better aggregate yields. Crop yields are composed of the weighted average of

²⁰ Although not realistic, this assumption is made for computational simplicity and tractability. It is also based on work by Freeman (2005).

²¹ Farmers who do not sell their plots and pass them down to next generation farmers as assumed to derive utility from passing down the greatest number of plots possible.

4 different crop types. That is, average yields realized by farmers with the same skill is the same for their given crop mix, *ceteris paribus*. Multiple crops in the mix are chosen in order to reflect realistic farm operations, including hedging against production and price risk. Diversification of crops is also necessary for crop rotational purposes. Total individual crop prices and yields for each farmer are composed of a weighted average of the four types of crops that are assumed to be grown. Equations 3.1 and 3.2 illustrate the relationship between individual prices (yields) and weighted average prices (yields) respectively;

$$P^t = \alpha P_1^t + \beta P_2^t + \delta P_3^t + \phi P_4^t \quad (3.1)$$

$$Y^t = \alpha Y_1^t + \beta Y_2^t + \delta Y_3^t + \phi Y_4^t \quad (3.2)$$

with $\alpha + \beta + \delta + \phi = 1$ and $\alpha, \beta, \delta, \phi > 0$.

Both prices, P_i , and average yields, Y_i , are assumed to be exogenously determined.

Yields are affected by random weather patterns and prices are determined in the world market - no one farmer has an influence on prices. As such, price and yield vectors are imported into the model.

Total production for farm agent k in year t is:

$$TP_k^t = M_k^t \cdot A_k^t \cdot Y^t \quad (3.3)$$

M_k^t , A_k^t , and Y^t are the annual multiplier of farmer k , cultivatable acres belonging to farmer k , and average yield in time t , respectively. The annual multiplier of farmer k is defined as:

$$M_k^t = \sum \left(PI_{xy}^t \cdot \frac{K_{xy}}{K_k^t} \cdot Sk_k \right) \quad (3.4)$$

where PI_{xy}^t is the productivity of plot xy in time t , equal to $(Rain_{xy}^t \cdot Quality_{xy})$

K_{xy} is the crop acres of plot xy

K_k^t is the total crop acres managed by farm agent k

Sk_k is the productivity (skill) measure for agent k

Total production for farmer k is a function of the number of cultivatable acres owned, average crop yield, and the annual multiplier of farmer k . The annual multiplier is a function of the farmer's skill, the quality of their cropland, and the weather variable (rain), while this latter is responsible for differentiating average yields between farmers. So part of the annual multiplier is random and exogenous (rain), while the remainder is dependent on a farmer's initial endowment (quality and skill).

Gross revenue received by farmer k in year t when price is equal to P^t is

$$GR_k^t = TP_k^t \cdot P^t \quad (3.5)$$

which is simply the total product produced by the farm agent on all plots of land managed multiplied by the exogenous price in that year.

3.5.2 Costs of Production

Total cost of production for farm agent k is composed of fixed and variable costs.

Variable costs are a function of area cultivated, yield realized, and distance from plot xy to agent k 's farmstead. Similar to the work of Freeman (2005), farm agents do not decrease variable costs incurred if yield is expected to be poor. Fixed costs are constant in year t but can vary across years t and $t + 1$ and include cost of capital, debt payments, and capital replacement. For simplicity, family/management living withdrawal is also considered as a fixed cost.

Variable costs are computed as the sum of all variable costs for all plots of land, $i_k = (1_k, \dots, I_k)$, managed by farm agent k in year t , and includes any non-family labour that is used;

$$VC_k^t = \sum_{i=1}^I (A_k \cdot (VC_i^{acre} + W) + V_i \cdot VC_i^{vol}) \quad (3.6)$$

where: A_k is cultivatable acres belonging to farmer k ,

VC_i^{acre} is the variable cost per acre of plot i

W is the non-family labour per acre for agent k

V_i is the production volume for plot i

VC_i^{vol} is the variable cost of production for plot i

Travel and transportation costs consist of the costs for farmer k to check on his crops as well as the cost of hauling the product back to the farmstead once it is harvested. Consequently, there is an incentive for farmers to purchase additional plots near to the farmstead as possible – and this effect will be captured in expected land values and bidding strategies. Total transportation costs are computed as the sum of the travel and trucking costs to all plots currently managed for agent k ;

$$TV_k^t = \sum_{i=1}^I TE_{xy} \quad (3.7)$$

and

$$TE_{xy} = D_{xy} \cdot (Travel + V_{xy} \cdot Truck) \quad (3.8)$$

where: TV_k^t is the total transportation costs incurred by agent k in year t
 TE_{xy} is the transportation cost associated with plot xy in year t
 D_{xy} is the distance from plot xy to farmer k 's farmstead
 $Travel$ is the annual cost of travel and transporting equipment per unit of distance
 V_{xy} is the volume of all crops (weighted average) of plot xy
 $Truck$ is the annual cost of transporting crop output per unit of distance

Thus, the total variable costs incurred by farmer k in year t are $VC_k^{Total} = VC_k^t + TV_k^t$. In order to calculate the total costs incurred by farmer k in t , fixed costs and family deductions must also be included. Since there is no land leasing market, there is no annual fixed cost to leasing land. As such, only the fixed costs of replacing machinery and buildings, family living withdrawals, and debt servicing payments are included in this simulation. And as mentioned earlier, lumpy investments are not modeled, but annual reinvestment requirements are set equal to the economic rate of depreciation.

$$FC^{capital} = C^{Replacement} \quad (3.9)$$

The family deduction is the minimum amount of cash that must be withdrawn from farm operation to cover living expenses, managerial costs, and family labour (Freeman, 2005). I assume here that farms do not have access to off farm income, allowing them to reduce their family deductions. All farms have the same minimum family

withdrawal and marginal propensity to consume from gross revenues. However, annual withdrawals increase in farm size as a result of additional managerial and labour burdens.

$$FW_k = FW_k^{\min} + \beta \cdot GR_k^t + \sigma \cdot K_k \quad (3.10)$$

where: FW is the total family withdrawal for farm agent k

FW^{\min} is the minimum family withdrawal amount for agent k

β is the marginal propensity to consume for farm agent k

σ is the management/labour cost adjustment for an additional plot of land

Total fixed cash commitment for a farm operator becomes;

$$FC_k^{Total} = FC_k^{capital} + FW_k + DebtService_k \quad (3.11)$$

where $DebtService$ is the total debt payment in time t . Therefore, total costs sustained by farm agent k in time t are $FC_k^{Total} + VC_k^{Total}$. Any revenues generated above and beyond this amount are carried over to year $t + 1$ and are subject to interest accrued. Once farmers have succeeded in saving a threshold level of cash and assets, they are able to seek out land to bid on in hopes of expanding their farm operations²².

3.5.3 Farm Exits and Farm Expansion

Over the course of their lifecycles, farm agents take part in production activities that may allow them to acquire the funds to purchase additional land, thus expanding their farm. It is assumed that in time $t = 0$ all farm land is owned, so for any one farm agent to purchase land in subsequent time periods, at least one other farm agent must be willing to sell land. Farm agents sell land when they exit the market. Market exit in the model occurs for one of 3 reasons - *Retirement*, *Forced Exit*, or *Voluntary Exit*.

Retirement occurs when farmers reach a critical age and no longer wish to farm. The probability of retirement increases in age. The retirement phase begins when farmers reach the age of 55 and ends with forced retirement at the age of 80. Forced exit occurs when a farmer fails a test for financial solvency - if a farmer has debt that exceeds 90% of their asset value, they are deemed insolvent and forced out of the market. Their land

²² Assuming that they are not in the Exit and Retirement phase of their lifecycles and have no children to pass the land on to; at which point farm agents attempt to save as much cash as possible for retirement.

is then sold on the open market. Voluntary exit occurs when a farmer calculates that it is no longer profitable to farm and chooses to exit to protect their equity. Farmers choose to exit the market when they have had Net Cash Flow Before Investment (NCFBI) < 0 for 4-9 (random) years in a row.

$$NCFBI_k = GR_k^t - (FC_k^{Total} + VC_k^{Total}) \quad (3.12)$$

After retirement or a voluntary exit, farmers can choose to sell their land on the open market or hand it down to an heir. The probability of farm take-over by an heir is set prior to initializing the model and remains constant throughout the simulation. In order for a farm to be taken over, farm equity must be at least 60% of farm assets. If this condition is met, a farm will be passed down to an heir with some predetermined probability, ρ . Again, if land is not passed down, it is sold on the open market. Here I also make the assumption of no “arms-length” sales, and all plots that are sold are sold on the auction block and there are no private sales.

Land that becomes available for purchase and is bid on by farmers aged 54 (or younger) who have been deemed credit worthy for a loan. Credit worthiness is determined by a debt to asset ratio (D/A ratio) check and a minimum amount of cash to cover down payment and cropping costs for the following year. Farmers also are monitored to ensure that expected production margins are sufficient to cover family withdrawals and future debt payments. Expected production margins are calculated as follows (Freeman 2005):

$$E[PM_t] = (1 - \lambda)E[PM_{t-1}] + \lambda PM_{t-1} \quad (3.13)$$

Farmers who meet all 4 criteria are free to make bids on available land. Issues surrounding bid formation and credit constraints are discussed below.

3.5.4 Expectation Formation

In light of the evolutionary characteristics of this model, farm agents will be forced to make a series of decisions over time; decisions that will affect their welfare, and the welfare of others in their local and global environment. In order to make these

decisions, it is important for farm agents to form expectations about a number of unknown parameters.

For instance, farmers who decide to buy (or sell) land will be forced to formulate expectations about future yields and prices to determine the expected profitability of a plot of land. The maximum willingness to pay (WTP) for a plot of land is based on expectations about future yields and prices, and the costs associated with these expectations. Price and yield expectations are formulated as follows²³:

$$E P_t = [\psi P_{t-1} + \nu P_{t-2} + \varpi P_{t-3} + \tau P_{t-4} + \Omega P_{t-5}] \cdot \varepsilon \quad (3.14)$$

$$E Y_t = [\psi Y_{t-1} + \nu Y_{t-2} + \varpi Y_{t-3} + \tau Y_{t-4} + \Omega Y_{t-5}] \cdot \varepsilon \quad (3.15)$$

with $\psi + \nu + \varpi + \tau + \Omega = 1$ and $\psi, \nu, \varpi, \tau, \Omega \geq 0$.

I assume that ε is decreasing in *Skill* level. In other words, for each agent the error term ε is independently and identically distributed each time it is used for calculation²⁴.

It is important to note differences in prices versus yields. Prices are a global parameter (the same for all agents) and thus all farmers will have the same information and predicted price in t . This price is then multiplied by ε to account for variations in expectations. Yields however, are a local parameter (they vary across agents) due to exogenous factors like weather and managerial skills. I assume that farmers only have yield information (or trustworthy yield information) for their own crops. As such, the information used by farm agent k will be the average of farm agent k 's yields for time periods $t - 1$, $t - 2$, and $t - 3$, $t - 4$, and $t - 5$ adjusted for the average soil quality of their land.

3.5.5 Land Market

The following will motivate a farm agent's decision to buy or sell land and discuss how a farm agent calculates their maximum willingness to pay (WTP) and minimum

²³ Equations 3.13-3.15 are based on the work of Freeman (2005) and were chosen because he found them to be acceptable means of formulating expectations when regional structural change in agriculture was examined.

²⁴ $\varepsilon \sim \eta(0, \omega)$ where ω is a function of skill. More details are available in the simulation code in Appendix A.

willingness to accept (WTA) for a plot of land²⁵. This section will end with a discussion about agent learning.

3.5.5.1 Maximum WTP, Credit Constraints, and Bid Formation

Since I assume that farm agents derive utility from acquiring as much land as possible, a farm agent's utility is based partly on their ability to make a few key judgments. Explicitly, these include calculating maximum WTP, deciding on an optimal bid, and learning from past experiences. Aside from a skill parameter that only affects agricultural production, farm agents are assumed to be homogeneous in other skills; this includes their ability to make the aforementioned decisions. As such, farm agents will only gain advantages over one another in their *experiences* and *learned price information* from experience. In effect, farmers who make these decisions more often will have more information on which to base future decisions, allowing them to make more accurate expectation calculations. Farm agents who meet all four criteria outlined in section 3.6.3 can take part in the land market as buyers and thus they need to make the following calculations.

When a buyer calculates maximum WTP, she uses her expectations about prices, yields, and the future price of land. Bidding more frequently allows farmers to obtain more accurate information about the expected price of land, and this can decrease error in maximum WTP estimation. Equation 3.16 illustrates this:

$$MaxWTP_k = [[PVInc. + E \text{ Re saleValue} - CapitalInvestment] \cdot \varepsilon] \cdot Risk \quad (3.16)$$

where:

- $PVInc. = \left[1 - \frac{1}{(1+r)^T} \right] \cdot \left[\frac{E[\pi]}{r} \right]$ and r is the interest rate, T is the year in which the agent expects to leave the industry. This is simply her discounted present value of expected future income streams.

²⁵ WTP is the amount that a farmer is the maximum that a farmer is willing to pay for a plot of land when purchasing it. WTA is the minimum a farmer is willing to accept in exchange for a plot of land when selling it.

- $E[\pi]$ is the annual expected net revenue of owning the plot of land, using expected prices and yields from (3.14-3.15) and adjusted for quality.

- $E[Re\,sale\,Value] = \left[\frac{V^T}{(1+r)^T} \right]$ and V^T is the expected price of land in T

calculated from learned information about prices. V^T is used to estimate the value of land in T since agents have no other information upon which to base an estimate. In effect, I am assuming that land in T will be valued the same as it is in t and only simply needs to be adjusted for the time value of money. Agent learning from experience in the auctions plays a large role in determining how well V^T is estimated.

- $CapitalInvestment = K_{xy} \cdot C$ where C is the non-land capital requirement per acre for land farmed.
- ε is defined as above
- $Risk$ is the risk aversion parameter associated with entrepreneurial attitude and is strictly < 1

Farmers are sometimes also constrained by a maximum borrowing limit. Similar to reality, I assume that farmers make a 25% down payment on any land purchases. This implies that farmers must borrow 75% of the purchase price from lending institutions. To that end, lending institutions place a maximum borrowing limit on farmers who wish to bid. This maximum borrowing limit is determined as follows:

$$MaxBorrow = \frac{MeanNCFBI \cdot \left[1 - \frac{1}{(1+r)^{20}} \right]}{r} \quad (3.17)$$

Where $MeanNCFBI$ is the average of a farmer's previous 5 years NCFBI, and r is the interest rate which in turn makes 3.17 the capitalized value of cash flows. $MaxBorrow$ represents 75% of the maximum credit constrained bid a farmer can make. Therefore, the maximum credit constrained bid is:

$$MaxBid = MaxBorrow / (1 - .25) \quad (3.18)$$

If $MaxBid$ lies below $MaxWTP$, $MaxBid$ becomes the upper bound for a bid; otherwise $MaxWTP$ is a farmer's upper bound.

Since farmers know their absolute upper bound for a bid, they must determine their valuation for a plot of land. In order to compute this, a farmer relies on prior experience and learned price information. Additionally, individual valuation is also determined by risk preference.

A farmer's risk aversion to losing an auction will be reflected in their valuation of the land. This type of risk is inversely related to expectation risk and is captured by placing upper and lower bounds on a farmer's expected value of land. This is shown in Table 3.1. Farmers in the Growth and Expansion Stage are considered to be the least risk averse farmers and aggressively seek to expand their farms. I assume that these farmers are the *most risk averse to losing* the auction. Farmers in the Development Stage still seek to expand, but not as aggressively. Finally, farmers in the Maintenance Stage still seek expanding, but do so very cautiously and are *the least risk averse to losing* of all farmers.

In this model no one farmer knows the value of a plot of land, and must rely on their learned information to estimate a value of a plot of land²⁶. Farmers will use their learned information to pick their valuation from a distribution of values, an idea motivated in part by the work on Bayesian updating by Zeng et al. (1998). These values are normally distributed about a farmer's learned mean price and standard deviation of land.

In order to reflect a farmer's risk aversion to losing an auction, these distributions are truncated as shown in table 3.1.

A farmer then selects a value, X , from the corresponding distribution. If X lies above the upper bound, X is set to $\text{Min}(MaxBid, MaxWTP)$, otherwise the estimated value of the land remains at X .

²⁶ Learned prices are adjusted to reflect different qualities of land.

Table 3.1 Farm Agent Valuation Distributions

	Distribution	Truncation	
Stage		Lower Bound	Upper Bound
Growth and Expansion	$\sim N(\text{Est.Mean}, \text{Est.Std.Dev})$	Mean - (1 Std.Dev)	Mean + (3 Std.Dev)
Development	$\sim N(\text{Est.Mean}, \text{Est.Std.Dev})$	Mean - (2 Std.Dev)	Mean + (2 Std.Dev)
Maintenance	$\sim N(\text{Est.Mean}, \text{Est.Std.Dev})$	Mean - (3 Std.Dev)	Mean + (1 Std.Dev)

Source: Author's calculations.

3.5.5.2 Reservation Price

All land that is submitted to auction by either retirees or voluntary exit farmers is assigned a reservation price and is put up for sale each period until it sells at a price equal to, or above its reservation price. I assume that farmers who are forced out of the market have all their assets, including land, repossessed and sold by the bank who then assigns a reservation price. Reservation prices are not revealed to the bidders at any point. Farm agents have incentives to receive the highest price possible for their land since the cash generated; 1) is an asset, and 2) goes towards retirement where more cash is desirable.

Reservation prices are calculated based on a seller's perceived price of land at time t . Perceived prices are a function of learned information about current average price per acre. Farm agent k will set

$$\text{MinWTA}_k = [\bar{V}_k^t \cdot Sk_k \cdot (1 - \omega)] \cdot \varepsilon \quad (3.19)$$

where \bar{V}_k^t is seller k 's learned price of land adjusted for acres and quality, and ω is a measure of urgency. I also assume that retired farmers frequently attend auctions seeking to sell their land, and that their price information, \bar{V}_k^t , is *at least* as accurate as the best informed farmer.

As a retiree becomes more urgent to sell their land, ω increases, leading to a reserve price decrease. Farm agents will have different degrees of urgency under different situations. The longer a plot is held for sale without being sold, the higher the seller's urgency. This is intended to capture the effect of retirees who are seeking to sell of all

their plots in a reasonable time so as to obtain the equity stored in these plots. Urgency parameters are distributed as follows:

Table 3.2 Distribution of Urgency Parameters

Years Retired	Urgency Parameter
≤ 2	0.85
> 2	0.80
> 5	0.75

Source: Author's Calculations

3.5.5.3 Farm Agent Learning

The breadth of the agent learning literature has already been discussed. This section will focus on agent learning mechanisms specific to this thesis. Once again, a number of assumptions are made in order to make the model tractable and I will highlight the features that have been deemed most important to this research.

The first set of assumptions concerns *what* agents can learn. All farm agents are assumed to have the capability to learn, and do so at an equal rate. Agents learn about prices of transacted land parcels, and how to increase 1) the probability of increasing rents when an auction is won, 2) the probability of winning an auction. Furthermore, agents only learn information after an auction has been closed. In other words, farm agents are not able to use price information (bids) in the same auction in which it was revealed²⁷. A second assumption I make is that for each auction, $m \in M$, only 1 plot of land is sold. There is a separate auction for each plot of land for sale. Finally, all auctions are assumed to be conducted precisely on the plot being sold. The location of any auction m is exactly equal to the (x,y) coordinates of plot xy being auctioned.

When agents learn, they will do so via two separate mechanisms called *Local* and *Global Learning* mechanisms. Local learning occurs when an agent participates in an auction; agent k is said to learn locally from auction m when she is a bidder in auction m . *Local Learning* takes place by means of two pathways; 1) *Price Information*, 2) *Optimal Bidding Information*. Price information learning means that agents

²⁷ This assumption is relaxed slightly for English auctions. This issue is discussed below.

participating in auction m learn the final price (Price Information) of the plot of land sold in auction m ²⁸. This information is perfect and known to all bidders in m . Optimal Bidding information is slightly more complex and is discussed in detail below.

Global Learning about auction m occurs for all agents who do not take part in auction m . All agents $k \in K$ who do not participate in m will receive final price information by means of a diffusion process. Specifically, final price information from auction m will diffuse through the population, getting noisier as the agent's distance from (x,y) increases, according to the following equation;

$$\bar{P}_{xy}^t(m) = P_{xy}^t(m) + \Pi(m) \quad (3.20)$$

where: \bar{P}_{xy}^t is the noisy signal heard by agent k from auction m

P_{xy}^t is the true final price of plot xy in auction m

$\Pi(m)$ is the noise term. This is $\eta(0, S(m))$ and $S(m)$ is increasing in distance from the location of auction m to the farm agent k .

It is important to note that all farm agents possess a limited memory. They are only capable of holding a finite amount of price and bid information. Once their memory capacity is full, new information replaces the oldest piece of information.

Optimal bidding is modeled after Neugebauer and Selten's (2006) Learning Direction Theory (LDT) and is a qualitative behavioural theory based on bounded rationality. LDT is motivated by *ex post* rationality and forces agents to ask themselves if a different action might have produced a better result.

For example, consider farm agent k who wishes to bid on plot xy during auction m . Agent k estimates her value, X , and depending on the auction mechanism used and her information, calculates her optimal bid $B(X)$. Now consider the following cases; 1) agent k wins the auction; and 2) agent k loses the auction.

Case 1: Agent k wins auction m in t and has incurred surplus S_1 . In her next auction agent k will bid:

²⁸ This is true only for auction designs that allow such information. i.e. sealed bid auctions only reveal the final price; where as an English auction reveals the bids and the final price.

- i) $B(X)$ with probability τ
- ii) $B(X) - \varepsilon \%$ with probability $1 - \tau$ so as to potentially receive more surplus

Case 2: Agent k loses auction m in t and bids $B(X) + \varepsilon \%$ in her next auction so as to increase her chances of winning in t .

The model will be simulated with and without LDT for each type of auction in order to determine the effects of LDT in this repeated game setting. I expect that incorporating LDT in the model will alter the results since agents are able to adapt and use *ex post* information to increase their chances of success. Understanding the effect of an adaptation and learning strategy in a repeated game setting is very important for auction design in land markets if optimality and efficiency are to be achieved.

3.5.6 Capital Investment

In cases where agents are successful in winning an auction and purchasing land, they must purchase additional non-land capital to farm that land. I assume that non-land capital requirements are perfectly divisible and that agents purchase only the quantity of capital they need. As in equation 3.16, agents will purchase additional non-land capital according to the following relationship so as to maintain the necessary non-land capital stock to acre ratio:

$$CapitalInvestment^t = C \cdot K_{xy} \quad (3.21)$$

3.6 Optimal Bid Formation

During the course of the simulation, I assume that all farmers will act similarly – regardless of the type of auction mechanism employed – to determine their maximum WTP and their estimated value of the plot of land. After this point however, farmers are assumed to formulate bids strategically depending on the type of auction mechanism they will face. This section will discuss the optimal bidding mechanisms used by farmers for each type of auction. These optimal bidding strategies are based on theoretical work in the auction literature. I offer that the bidding model proposed here is too mathematically complex to derive an agent's optimal bid analytically, so I need to approximate bid behaviour using known bidding algorithms that are easily

computable. Ease of computation is especially important because optimal bidding strategies should be tractable in real world settings²⁹.

Before beginning, I shall discuss a few assumptions I have made that are common to all auctions. First, farmers will be made aware of the number of bidders participating in the auction. Secondly, if an auction has only 1 bidder, it automatically converts to a bargaining solution between the bidder and the seller where the final price paid is the mid-point of the bid/ask spread so long as the initial bid is above the reservation price. Lastly, any Third-Price-Sealed-Bid auction with less than 3 bidders is not carried out and the land is not sold.

3.6.1 First-Price-Sealed-Bid (FPSB) Auction

In a FPSB auction, farmers submit a sealed bid to the auctioneer. After all bids have been received, the auctioneer ranks all bids and awards the plot to the bidder with the highest bid at the price they bid. It is commonly known in auction theory that in a one-shot or static FPSB, agents have incentives to bid below their valuation of the good if they believe they can submit a winning bid that is just higher than the next highest bid. Therefore, bidders trade-off increasing their probability of winning the auction with reduced surplus received from a win. That is, as their bids increase they have a higher probability of winning but will receive less surplus because the transaction price is closer to their actual valuation.

In order to capture this, farmers in this simulation will bid according to the following rule (which is the optimal bidding scheme for this auction under IID assumptions - see Kagel and Levin 1993).

$$B(X)_1 = X(N-1)/N \quad (3.22)$$

²⁹ Optimal bidding functions used herein are based on well-known best-response functions in theoretical auction literature (Kagel and Levin 1993). As noted above, these functions are not optimal in a mathematical sense, but are aligned with incentives that all bidders are assumed to have. It should also be noted that the bidding functions used in this thesis are not likely to affect the outcome of the auctions relative to the case where agents bid their WTP. The optimal bidding functions employed in this model serve as a tool for agents to bid strategically. Bidding via optimal best-response functions lowers average price in auctions, thus yielding more buyer surplus. They should not affect the outcome of the auction or the general outcome of the simulations because the agent with the highest WTP always wins.

where X is a farmer's value for the plot of land and N is the number of bidders bidding on the plot of land. Clearly, as the number of bidders increases, the bid approaches the farmer's true value. This incorporates the notion that as N increases, farmers must bid higher in order to increase the probability that their bid will be the highest.

3.6.2 Second-Price-Sealed-Bid (SPSB) a.k.a. Vickrey Auction

The strategy in a SPSB is similar to that of a FPSB except that in a SPSB farmers have the incentive to bid their true valuation, X , for the plot of land (Vickrey 1961). This occurs because the price that the winning farmer pays is not a function of her bid. A winning bidder will pay the second highest bidder's bid, thus she has no incentive to increase or decrease her bid above or below her true valuation. As such, in a SPSB we have

$$B(X)_2 = X \quad (3.23)$$

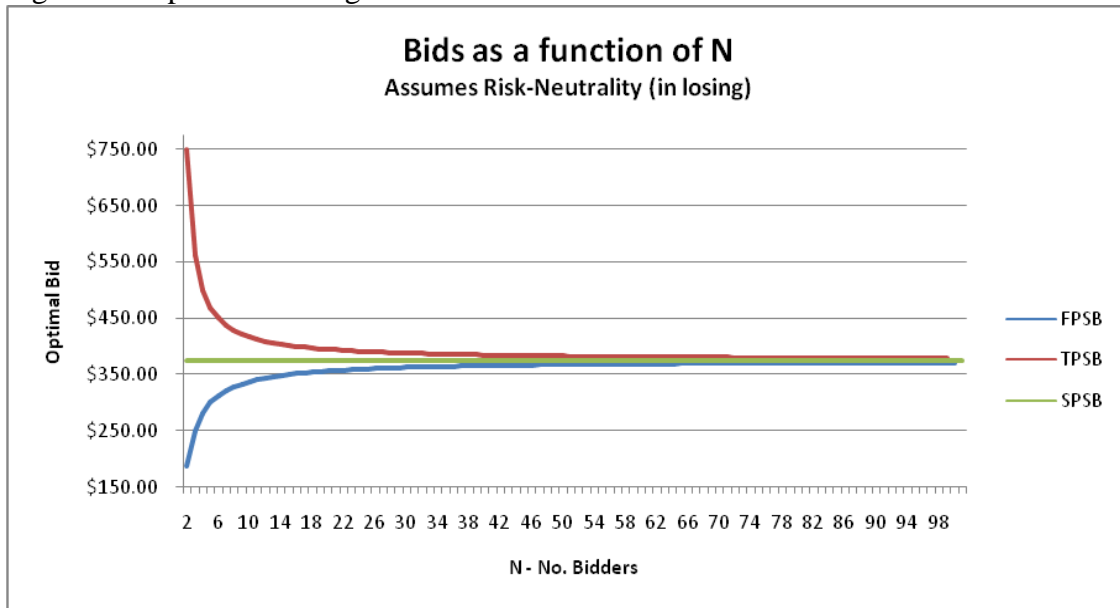
3.6.3 Third-Price-Sealed-Bid (TPSB) Auction

A TPSB is again similar to the FPSB and SPSB auctions in that it is a single round sealed bid. However, in a TPSB the bidder with the highest bid does not pay their bid, nor the second highest bid, but the third highest bid. In this case the winning bid will be above X and is decreasing in N . For more information regarding this bidding scheme see Kagel and Levin (1993). In effect, bidders in the simulation will bid according to the following formula;

$$B(X)_3 = X(N-1)/(N-2) \quad (3.24)$$

For comparative purposes figure 3.2 shows the optimal bid functions for all 3 sealed-bid auctions assuming agent k has a value $X = 375$.

Figure 3.2 Optimal Bidding Schemes for Sealed-Bid Auctions



3.6.4 English Auction

The English auction bidding mechanism is the most difficult of the auctions to model because this type of auction is evolutionary and subject to feedback – farmers have the ability to make a bid, then re-evaluate their bid based on other farmers’ observable bids and submit a new, higher bid, if desired. In addition, there is a very subtle but important element in the English auction mechanism that is not observed in the sealed-bid auctions – revelation of others’ bids.

The structure of the sealed-bids auction means that bid re-evaluation is not possible. But I argued earlier that farmland is a good with affiliated-values elements. In effect, knowing that another agent values the land more (or less) than you do can affect whether or not you submit another (higher) bid in the English auction.

For computational purposes several assumptions about the rules of this English auction are different than a typical English auction. Nevertheless, the auction algorithm used here captures all the important components of an English auction.

Bidding is divided into 2 rounds. In the first round, all bidders are assumed to submit oral bids until the bid reaches their personal valuation for the good, $B(X)$. At this point, the bidder with the highest valuation will have submitted a bid equal to the second highest bidder's bid plus a minimum bid increment, ζ , and thus would be considered the winner of the auction. Up to this point we have an auction that resembles the SPSB.

But after the first round of bidding, all farmers are allowed to re-evaluate the common-value element of their bid now that more information is available. This occurs because of the affiliated-values assumption on farm land. If they have reason to believe that they have undervalued the land, farmers may choose to submit a new, higher bid. Those who do not submit a new bid drop out of the auction.

A farmer will increase her valuation, and her bid, for the plot of land to her MaxWTP (if her MaxWTP is greater than the current winning price) with some probability ρ . In turn, the probability that a farmer will choose to increase her valuation is dependent on her risk preferences. As described earlier, farmers in the *Growth and Expansion Phase* are more risk averse *to losing* the auction than a farmer in the *Maintenance Phase* and will subsequently have a higher probability of increasing their valuations to MaxWTP³⁰.

Once all farmers have determined whether or not to increase their valuation, bids are submitted again. The farmer with the highest MaxWTP wins the auction and pays the second highest MaxWTP + ζ . Finally, note that the probability of bids increasing past farmers' valuations to their maximum WTP is dependent on the number of bidders in an auction *and* the risk preference of those bidders.

3.6.5 Summary of Optimal Bidding Schemes

It is easy to see that different auction mechanisms would affect resultant bids in different ways if auctions were highly formalized and individual bids were always optimal. What is more interesting is how these “less than optimal”, but theoretically

³⁰ It should be noted that farmers do not change their risk preference, but are more or less likely to change the common-value element of their valuation based on their preferences towards risk, and losing an auction.

accepted static bidding algorithms fare in a dynamic environment with feedback and learning. Current theory is unable to tell us what will happen to prices and stability when the auction environment is analytically complex and evolutionary.

CHAPTER 4

MODEL INITIALIZATION AND DATA

4.0 Introduction

"Our simulations are not meant to replicate the price dynamics observed in real markets, but to compare the performance of three different mechanisms given the same flow of orders." - Pellizzari and Dal Forno (2007)

Until this point, this thesis has outlined the theory and the structure of the behavioural and financial equations that form the backbone of this simulation model. A simulation model however, requires data for initialization both for endogenous and exogenous variables. This chapter will discuss the data used to initialize the model, as well as the methods by which the data were generated. It is important to note that since the focus of this thesis is on the auction mechanisms used by farmers for land transactions, it is essential that a stable global simulation environment be created. This stable environment ensures a *ceteris paribus* situation that farm agents need only react to farmland price fluctuations, information about farmland prices, and the auction mechanism. By eliminating factors such as boom/bust crop cycles, proper initialization will more accurately allow us to focus on the desired behaviour. Therefore, unlike previous related work by Freeman (2005), I will utilize an artificial set of prices, yields, and farm profiles to ensure long term market stability.

Netlogo© version 3.1.3 was the MAS simulation platform chosen for this analysis. This software offers a number of advantages over other MAS simulation packages commercially available – most notably ease of use and simple programming functions. Netlogo© is a windows based software that is provided free of charge from Center for

Connected Learning and Computer-Based Modeling in the Department of Computer Science at Northwestern University in Evanston, Illinois³¹.

4.1 Initialization of the Model

Each iteration of the simulation begins with a similar market structure. Farm operator attributes including; 1) age, 2) farm size, 3) attitude, 4) financial information, and 5) learned price information are homogeneous across iterations. In other words, between simulations of the same auction type, the only factors that change are the location of the farmsteads and the location and quality of the owned plots of land³².

4.2 Initial Farm Population Profile

This section discusses in detail those variables that constitute the initial farm profile, including their distributions, and methods used for their generation. All data is adjusted with 2004 prices and was created with a random number generator using estimated means and standard deviations compiled from a variety of sources.

4.2.1 Operator Age and Cultivated Acres

Farmer age and land area owned were generated by means of a random number generator. Here, farmer age is distributed as η (38.2, 9.32) while plots owned is η (10.0, 5.94). Means and standard deviations were estimated using data from various census agricultural regions in the 2005 Farm Financial Survey (FFS). The simulation is initialized with 422 farmers with a mean age of 38 and an average farm size of 1600 acres. Plots owned by age category are shown in table 4.1.

³¹ For more information see <http://ccl.northwestern.edu/netlogo/>

³² Altering the landscape between iterations of the simulation will have little impact on the results. Running 100 iterations of each simulation also mitigates any such adverse effects. Further discussion and analysis is left to future research endeavors.

Table 4.1 Distribution of Initial Plots Owned by Age Group

Age	Plots Owned				
	1 to 5	6 to 10	11 to 15	16 to 20	21 +
20 - 29	15	20	25	17	4
30 - 39	24	52	38	22	10
40 - 49	49	49	37	13	9
50 - 59	9	16	6	0	0
60 - 69	5	2	0	0	0

Source: Author, based on information from 2005 FFS

4.2.2 Operator Assets and Debt

Initial farm agent assets are equal to the sum of all machinery, land, and cash held at $t = 0$. Cash accounts are initialized at \$75.00 per cultivatable acre while capital stocks, which include machinery, equipment, and buildings, are initialized at \$100.00 per cultivatable acre. Note that learned price information at time $t = 0$ is adjusted for plot quality = 1 so that it reflects prices for land of average quality. Information regarding the Learned Price Information at time $t = 0$ will be described in subsequent sections. Cash accounts and capital assets are based on values from Freeman (2005) and adjusted to reflect 2004 prices.

Farm operator debt per cultivatable acre was calculated based on estimated means and standard deviations from various census agricultural regions in the 2005 FFS. Farm operator debt per acre is distributed as η (101.77, 49.48). This translates to an average farm indebtedness of \$165,643. Total farm indebtedness at time $t = 0$ for all 422 farmers is \$69,901,243. A breakdown of farm debt by age group is shown in table 4.2.

Table 4.2 Initial Farmer Debt by Age Group

Age	Debt (thousands)				
	0 to \$50	>\$50 to <\$100	\$100 to <\$300	\$300 to <\$500	\$500 +
20 - 29	13	14	42	10	2
30 - 39	31	19	69	24	3
40 - 49	37	29	65	23	3
50 - 59	7	9	14	1	0
60 - 69	5	2	0	0	0

Source: Author, based on information from 2005 FFS

4.2.3 Risk Attitude and Entrepreneurial Classification

This section is also based on work by Freeman (2005) and has been adapted for the purposes of this thesis. As previously noted, I assume age determines a farmer's risk attitude and managerial characteristics. Most importantly, risk attitude determines how risk averse a farmer is when calculating their MaxWTP and estimating their value of the land bid. Growth and Expansion farmers will discount their MaxWTP less than farmers in other phases and will have a greater probability of attaching a high value to a given plot. This gives a farmer in the *Growth and Expansion* phase a higher probability of winning any given auction, but can also lead to over estimation of land values and over bidding. As age increases, farmers are less likely to over value and over bid on land, but they are also less likely to value land high enough to out bid aggressively expanding farm agents. Table 4.3 summarizes the managerial behaviour of farmer in each of the 4 phases.

Table 4.3 Managerial Classification

Managerial Classification	Expectation Behaviour	Bidding Behaviour	Risk Aversion Factor
<i>Growth and Expansion</i>	<i>Least Risk Averse</i>	<i>Most Risk Averse To Losing</i>	0.95
<i>Development</i>	<i>Intermediate Risk</i>	<i>Intermediate Risk To Losing</i>	0.90
<i>Maintenance</i>	<i>Most Risk Averse</i>	<i>Least Risk Averse To Losing</i>	0.85
<i>Exit and Retirement</i>	<i>All Farmers Aged ≥ 55</i>	<i>N/A</i>	0.85

Source: Author, adapted from Freeman (2005).

4.2.4 Initial Learned Price Information

Economic theory suggests that the price dynamics observed under varying auction mechanisms are likely to be different. As such, it is necessary to initialize farm agents' memories (Learned Price Information memory banks) with a set of past land prices for each auction. Farm agents are initialized with Learned Price Information for $t < 0$ using the following methodology.

I simulate 50 iterations of 35 years for each of the 4 types of auctions. This generates 1750 years of price information. After all the information has been gathered, the first 10 years of each simulation are dropped, leaving 50 iterations of 25 years, or 1250 years of

price information for each type of auction. Means and standard deviations are then estimated and a series of land prices are generated with this data. Once land prices have been generated for each type of auction using the auction specific means and standard deviations, these prices are sorted and compared against the simulated prices to remove any outliers. Finally, 100 randomly generated prices for each auction are selected and entered in to the farm agents' Learned Price Information memory bank. Table 4.4 reports the means and standard deviations of the generated prices for each type of auction. It is important to note that like age, farm size, and financial information, the Price Information is homogeneous across iterations of the same auction type.

Table 4.4 Initial Learned Price Information

	Initial Learned Price Information			
	English	FPSB	SPSB	TPSB
Mean	\$ 478.27	\$ 462.54	\$ 396.58	\$ 436.69
Standard Deviation	\$ 48.89	\$ 27.05	\$ 39.47	\$ 38.70
Maximum	\$ 580.54	\$ 511.83	\$ 468.66	\$ 503.51
Minimum	\$ 389.97	\$ 415.83	\$ 322.28	\$ 357.12

Source: Author's calculations.

4.3 Production Data

This section will describe the data used for farm production activities. This includes all input and output prices, and quantities, and the methods under which they were generated. This data is used to generate cash flows both in and out of the farm household. Technology and inflation are assumed constant through the simulation and all prices are adjusted to 2004 levels.

4.3.1 Crop Mix, Yields, and Prices

4.3.1.1 Crop Mix

Farmers are assumed to produce four crops - wheat, barley, peas, and canola. A farmer with $Skill = 1$ will produce these crops based on the percentages in table 4.5.

Recall that farmers with $Skill > 1$ are capable of making better managerial decisions than farmers with lower skill. I will assume that each farmer can adjust (implicitly) their crop mix to realize higher yields. For instance, a farmer with $Skill = 1.04$ receives a 4% higher yield than a farmer with $Skill = 1$. This results in higher gross revenue and higher NCFBI.

Table 4.5 Crop Mix Weights

Crop Mix Weight	Crop
40%	<i>Wheat</i>
15%	<i>Barley</i>
30%	<i>Canola</i>
15%	<i>Peas</i>

Source: Author's calculations

4.3.1.2 Generated Prices and Yields

In keeping with the need for a stable simulation environment, yearly crop prices and yields were generated in such a manner as to maintain constant long term trends with year to year price fluctuations. *Ceteris paribus*, a constant trend line is required to identify which auction mechanisms adjust to minor fluctuations in crop variables more readily, so that any observable trends in land prices as a result of exogenous crop price and yield information can be ruled out.

Crop prices and yields used in the simulation were generated by assuming a crop mix as in Table 4.5 and analyzing price and yield data from Saskatchewan Agriculture, Food, and Rural Revitalization for the 4 crops during the 1985-2004 cropping years. Crop yields and prices for the 4 crops were used to generate means and standard deviations for each crop. The data was then combined into a weighted average price and yield for the crop mix in Table 4.5 based on equations 4.1 and 4.2. From this process, prices and yields were randomly generated. Minor adjustments were made to the data to ensure stability and remove any outliers. A full breakdown of crop price per acre and yield per acre are available in Appendix A.

$$\frac{\$^t}{\text{ton}} = .4 \cdot \text{PriceWheat}^t + .15 \cdot \text{PriceBarley}^t + .3 \cdot \text{PriceCanola}^t + .15 \cdot \text{PricePeas}^t \quad (4.1)$$

$$\frac{\text{tons}^t}{\text{acre}} = .4 \cdot \text{YieldWheat}^t + .15 \cdot \text{YieldBarley}^t + .3 \cdot \text{YieldCanola}^t + .15 \cdot \text{YieldPeas}^t \quad (4.2)$$

As noted earlier about $t = 0$ in the simulation, farmers will require information about past crop prices and yields in order to form expectations. As a result, farmers are initialized with price and yield information corresponding to years $t = -5$ to $t = -1$.

4.3.2 Costs of Production

Production costs are developed in a similar fashion as Freeman (2005), with variations made for assumptions specific to this thesis.

4.3.2.1 Fixed Costs of Production

Fixed costs of agricultural production include farm machinery, equipment, and building replacement costs and debt servicing. Again, since it is assumed that investment in machinery, buildings, and equipment per cultivated acre remain constant throughout the simulation, the annual cost of capital replacement is \$100 multiplied by the rate of economic depreciation (Freeman, 2005).

Annual debt servicing costs are calculated at the beginning of each year and include all debt that is currently held by farm agents. All farm debt is treated identically, whether it is for capital purchases or land. Farmers carry one debt account which is refinanced each time a purchase is made. As mentioned earlier, farmers are assumed to pay a 25% down payment on any new purchases and finance loans based on a 20 year amortization period. Interest is assumed to accrue at 8%, compounded annually on the balance of the debt account.

4.3.2.2 Variable Costs of Production

Variable costs of crop production include the cost of production per acre, and transportation costs per ton. As in Freeman (2005) I assume that costs of production do

not vary with yield. In other words, farm agents have no foresight and do not cut costs if yields are expected to be low.

Costs per acre of production include both hired labour and variable production cost. Variable production costs were estimated using Saskatchewan Agriculture, Food, and Rural Revitalization's Crop Planning Guides (2004-2007) for Dark Brown Soil Zone conventionally seeded stubble crops. Total variable costs are calculated by summing the weighted variable production costs for each of the crops seeded and multiplying that by the total acres cropped by each farmer. Estimated variable costs per acre for each crop, and in total, are listed in Table 4.6³³.

Table 4.6 Variable Production Costs per Acre

Mix Weight	Crop	Cost/Acre
40%	<i>Wheat</i>	\$ 79.98
15%	<i>Barley</i>	\$ 77.51
30%	<i>Canola</i>	\$ 101.07
15%	<i>Peas</i>	\$ 81.39
100%	TOTAL	\$ 86.15

Source: Author's Calculations based on data from Saskatchewan Agriculture, Food and Rural Revitalization 1985-2004

Hired labour costs, W , are derived from Freeman (2005) and are adjusted for inflation. Total hired labour for each farm agent is calculated as in (4.3) and is a function of total acres cropped, K . As can be seen, total cost of hired labour is characterized by a logistic growth function and is plotted in Figure 4.1. It is clear that the cost of hired labour increases drastically when farm size reaches 600 acres. This is because the farm household is typically no longer able to provide the majority of the labour and must hire off-farm labour in order to continue with production activities.

$$W = \left[\left[0.03 + \frac{0.8}{1 + 14500 \cdot e^{-0.009 \cdot K}} \right] \cdot K \right] \cdot 6.75 \quad (4.3)$$

³³ Variable costs are estimated by subtracting custom work and hired labour, crop insurance premiums, utilities and misc., and interest on variable expenses from Sask Ag and Food's estimated costs.

Figure 4.1 Hired Labour Costs by Acres Cropped



4.3.3 Family Withdrawal

Family living expenses and managerial withdrawal are also based on Freeman's (2005) work but have been adjusted here to reflect a higher minimum withdrawal - \$30,000. Family withdrawal, FW is a function of both gross revenue, GR and acres cropped, K . See equation 4.4.

$$FW = 30,000 + (0.068 \cdot GR) + (0.834 \cdot K) \quad (4.4)$$

As noted by Freeman (2005), FW is characterised by an L -shaped curve that represents economies of scale.

4.4 Summary

This chapter discussed the data that will be used for the initialization of the MAS simulation model, as well as yearly exogenous price and yield information. The data and data sources presented in this chapter were chosen in order to ensure that the model reflects, as closely as possible, a representative sample of the grain and oilseeds farming sector in Saskatchewan, Canada.

CHAPTER 5

MEASUREMENT AND ANALYSIS

5.0 Introduction

“... (the) equilibrium approach lends itself to expression in equation form. And because an equilibrium by definition is a pattern that doesn’t change, in equation form it can be studied for its structure, its implications, and the conditions under which it obtains.” - Arthur (2005)

This section will introduce concepts of economic efficiency and discuss which measures of efficiency can and cannot be used for analysis of complex dynamic economic systems. Particular emphasis will be placed on measures of pricing efficiency, surplus, and industry level indicators. This section will begin with a discussion of classical economic tools used for this kind of analysis, followed by an introduction to alternative tools that might be used in complexity modeling. After this, measures of industry performance and system evolution will be discussed.

This section will refer to classical analysis in terms of equilibrium methods or steady state analysis, since the majority of neoclassical market analysis is grounded in equilibrium concepts. Even so, work done in the absence of such assumptions (e.g. dynamic macroeconomic systems) still assumes that there exists a set of underlying equations, including “equations of motion” which describe exactly the behaviour of a dynamic system over time. However, in complex systems analysis, underlying analytic relationships are unobservable due to the presence of feedback and individual interdependencies in the systems. Therefore, when considering complex system models such as this one, it is not feasible to use traditional economic tools to measure efficiency because economic equilibria are unobservable (Arthur 2005). In effect,

discussions in this section take as given the understanding that in or out of equilibrium, classical models rely upon assumptions that are not realistic when the system is actually complex in a mathematical sense.

5.1 Definitions of Market Efficiency

Much of neoclassical economic analysis is founded on the identification of efficiency, whether it is in production, trade, etc. The following sections will define and discuss various perspectives of economic efficiency and their place in different threads of economic literature, both classical and evolutionary.

5.1.1 Efficiency in Neoclassical Economics

To start, much of the work on neoclassical market structure is based, at least in part, on assumptions of perfect competition. The assumptions of perfect competition are the following; 1) the existence of many buyers and sellers, none of which have a large share of the market; 2) the production of homogeneous goods; 3) perfect information for all agents; and 4) free entry and exit (Case et al. 2001). Collectively, these factors ensure tractability and lead to equilibrium states where goods are traded at $P = MC$ ³⁴. In this spirit, measures of economic efficiency are typically derived from static equilibrium/steady states. When assumptions about information and homogeneity are relaxed, finding satisfactory measures of economic efficiency can be very difficult because the underlying system may be complex and not yield observable equilibria. In this case, traditional static equation based analysis of efficiency is no longer viable.

5.1.2 Neoclassical Auction Theory

In much of auction theory, the term *optimal* has been used to mean maximizing seller revenues. A good deal of the literature has focused on designing optimal auction mechanisms that will produce the highest possible selling price (the alternative use of these mechanisms is in the event of some sort of market breakdown – e.g. buyer

³⁴ Furthermore, in the absence of perfect competition, i.e. monopoly markets, an equilibrium set of prices and quantities is generally assumed to exist.

collusion as a result of thin markets³⁵). Efficient auctions are often considered to be those in which the bidder with the highest value for the good has the proper incentives and information to produce the highest bid.

Despite efforts, auction theory has not been very successful in expanding the optimal auctions research to problems that include combinations of heterogeneous bidders/goods, affiliated values, imperfect information, and/or repeated games and learning. In fact, Dasgupta and Maskin (2000) show that under the assumption of affiliated-values, current methodologies cannot adequately describe solution concepts. In effect, deriving an efficient/optimal auction in this case relies on making assumptions that ensure a static “steady-state” condition can be achieved. In other words, efficiency and optimality are measured against some sort of *assumed* equilibrium state, generally a Nash equilibrium³⁶.

While I acknowledge the work done on dynamic sequences of well-defined allocations in analytic economics, the focus of this thesis is on analytically complex markets that are in constant disequilibrium and may never converge. To that extent, a lack of convergence, together with unobservable structural equations, leaves traditional measures of efficiency and optimality without explanatory power.

5.1.3 Dynamic Trading Mechanisms

In recent years, there has been a trend towards identifying measures of efficiency in dynamic evolutionary models that are analogous to those developed for static models. In this thesis, the need for such measures results from out-of-equilibrium modeling techniques inherent in multi-agent simulations. Out-of-equilibrium economic models are especially important to develop since we rarely observe equilibrium steady states in nature. Consequently, understanding the complexities of out-of-equilibrium dynamics

³⁵ A market is referred to as thin when there are few bidders present. Alternatively, a thick market contains many bidders. The degree of thickness of a market is dependent on the type of market and the good to be auctioned. There is no specific number of bidders for thickness to be achieved that is common to all auctions.

³⁶ In some sense, the formation of auction markets due to normal market failures could be seen as self-organizing behaviour and movement towards an equilibrium market *structure*. However, this thesis is interested in steady states and equilibrium within a particular market structure, not as a market structure.

and evolution is important in the development of economic systems analysis (Arthur 2005). Arguably, one of the most important elements of out-of-equilibrium dynamics is system performance, or lack thereof. Since traditional economic measures of efficiency and performance often rely on an assumption of equilibrium states, there is a clear need to find alternative measures of performance and efficiency for out-of-equilibrium modeling.

At this point, I must note that in cases where out-of-equilibrium systems actually converge, or stabilize, classical economic measures of efficiency may suffice, provided the system is not complex and structural equations can be estimated (Arthur 2005).

While there have been prior attempts to measure performance and efficiency in dynamical economic systems, much of the work has been developed using ideas from financial analysis. For instance, the work of Pellizzari and Dal Forno (2007) offers a few suggestions that will prove useful. They state that in the absence of static equilibrium, one should be interested in “provision of liquidity, continuity, and price stabilization”. These concepts are also echoed by Madhavan (2000). In general, measures of price stability, convergence, and speed of convergence have been found in the financial literature to be acceptable measures of a system’s ability to evolve under exogenous shocks.

5.2 Measureable Criteria

In light of discussions about measures of efficiency under neoclassical assumptions, auction theory and dynamic trading mechanisms, it is time to develop measures of efficiency in the simulated auction market for farmland. This section will serve as an overview of the methods that will be employed in the thesis.

This simulation model incorporates a number of dynamic elements that render traditional neoclassical measures of efficiency obsolete. For example, there is no observable equilibrium price (one price does not fit all) and there are considerable out-of-equilibrium dynamics. In addition, unknown *ex post* realization of surpluses from the consumption of the good make traditional efficiency measures impractical.

5.2.1 Allocative Efficiency

Traditional measures of allocative efficiency applied to this simulated auction market require that bidders with the highest valuations for a good receive the good at the end of the auction, regardless of the price paid. As a result of the assumptions made for this farmland auction market, this outcome occurs with 100% certainty. This means from an allocative standpoint, all auction mechanisms compared in this study are by definition 100% efficient³⁷. However, standard measures of efficiency say nothing about the accuracy of the agents' valuations, a factor that is often assumed away under perfect information.

If we consider an alternative description of allocative efficiency in this auction context, an auction is not allocatively efficient if there exists uncertainty in the common-value element of the affiliated-values signal (Goeree and Offerman 2002). From this standpoint, the auctions compared in this thesis may or may not be efficient. Simply put, due to the nature of the land market, and the *ex post* realization of value, it is not possible to know if a farm agent's valuation was correct³⁸. Therefore, minimizing variance in auction sale prices has been suggested as one metric of minimized efficiency losses from an allocative standpoint (Goeree and Offerman 2002). To that extent, it will be possible here to *ordinally rank* the auctions based on allocative efficiency by measuring price variance in each simulated auction. And using Harberger's (1971) third welfare postulate, I can also rank auctions based on their surplus generating capabilities.

5.2.2 System Surpluses

Market efficiency is often measured by an economic system's ability to generate maximum social welfare (or total system surplus). By definition, a static economic

³⁷ This result says nothing about a farmer's ability to generate wealth from any plot of land however. Although a farmer may value the land the most, he or she may not have the highest *ex post* wealth generating capabilities. This is due to valuations on plots being sampled randomly from an agent-unique distribution it is possible that any farm agent can over estimate the value of any plot of land.

³⁸ Recall that agents form expectations about future prices and yields, and the future price of land. And since the full value of a capital asset (farmland) is based on future income streams, it is not possible for agents to know the true value of any plot of land until it is sold and income no longer is generated from it.

equilibrium is efficient if total surplus (= consumer + producer surplus) is maximized and $WTP = MC$. However use of such a measurement criteria often requires the existence of an equilibrium state and price, something that is unobservable in our dynamic, out-of-equilibrium land auction market.

In the absence of a static equilibrium, it is still possible to measure an agent's perceived surplus from a transaction in this simulation. In this model, transaction surplus is "perceived" because agents do not know with certainty the true value of the land purchased until it is no longer farmed and subsequently sold. Their best estimate of true value is the transaction price. Therefore, calculations of perceived surplus will be made based on the best information available in the current period – that is, the transacted price for land. This can be considered an *ex ante* calculation of surplus since the true *ex post* value of land is unknown.

In the simulation, buyers will observe a perceived surplus equal to their MaxWTP (upper bound) less the price they paid, while sellers perceive their surplus as their reservation price less the sale price. Perceived surplus will then be used to examine both the total surplus generated by an auction, as well as the shares of total surplus generated by an auction.

With reference to Harberger's (1971) first and second postulates concerning applied welfare economics, perceived surpluses will be summed and buyer/seller shares of surpluses will be compared to rank auctions based on equity. This is possible because, as noted by Harberger "the competitive demand price for given unit measures the value of that unit to the demander" and alternatively, "the competitive supply price for a given unit measures the value of that unit to the supplier". Under this framework, it is not necessary to observe equilibrium prices and quantities in the classical static sense. We simply observe prices, and those prices are the true value of that good at the time of purchase.

Total perceived surplus in each of these auctions will be compared in order to measure auction efficiency. To justify this, we refer to Harberger's (1971) third postulate – distributive neutrality - which suggests that a dollar is worth a dollar, regardless of who

it belongs to. To that extent, the auction that generates the most total perceived surplus will be considered the most efficient³⁹.

In spite of the latter postulate, I will also compare shares of perceived surpluses because this may be important from an agricultural policy perspective in future land markets. And although I make no claim about what is a fair distribution of surplus between buyers and sellers, knowing if an auction favours one of the transacting parties may be useful for future agricultural policy considerations.

5.2.3 Market and Price Stability

The majority of the efficiency measures developed for comparative purposes in out-of-equilibrium models to date are found in the financial market literature (see Pellizzari and Dal Forno 2007 for examples). Given the structure of the auction markets developed here, such out-of-equilibrium analysis will be necessary if any conclusions about market efficiencies are to be drawn or constructive suggestions made about the structure of these markets. As a result, the simulated auctions will be compared using measures of price stability as discussed in Pellizzari and Dal Forno (2007) and Madhavan (2000). Specifically, price level and variance over time will be used to evaluate market efficiency for each auction.

5.2.4 Industry Characteristics and Evolution

A final point of comparison will examine to what extent, if any, choice of auction mechanism has on industry evolution at a macro level. Macro level market characteristics such as farm exits, farm size, financial ratios, and bidder participation will be tracked to determine the impact auction design has on the evolution of this agricultural sector.

³⁹ It should be noted that in financial markets, there is a thread of literature that deals with “informational efficiency”. This type of efficiency assumes that as WTP and WTA converge, market efficiency increases because information is being used more efficiently. Although interesting, this analysis is not considered in the thesis.

5.3 Summary

Chapter 5 outlined the criteria by which traditional markets and efficiency in static economics are evaluated, in contrast to the criterion by which markets in this dynamic simulation model will be evaluated. This section has motivated various criteria under which the results for chapter 6 will be analyzed and from which conclusions in chapter 7 will be drawn.

CHAPTER 6

RESULTS AND INTERPRETATION

6.0 Introduction

This section discusses the results from the eight land auction simulations developed for this analysis. Initial parameters are set as discussed in Chapter 4. The only differences between simulations runs are the type of auction mechanism employed, and whether or not Learning Direction Theory (LDT) is activated or not (“On” or “Off”). When LDT is “On” agents are assumed to learn based on the algorithm outlined in Chapter 3. When LDT is “Off”, agents do not learn via LDT and are limited to simple information diffusion. Comparing similar auctions with LDT “On” and “Off” will help determine the effect that LDT has on each of the compared auction mechanisms. Table 6.1 shows the combination of auction mechanisms and LDT options comprising the eight simulations.

Table 6.1 Simulations Run

Type of Auction	Learning**		
		LDT "On"	LDT "Off"
	English	1	2
	FPSB	3	4
	SPSB	5	6
	TPSB	7	8

* Information Diffusion remains “On” at all times

** LDT – Learning Direction Theory.

Each of the simulations is run for 35 years – 1 year is equivalent to 1 cropping and harvest year – and re-run for a total of 100 iterations. This yields 3500 years of data for each of the 8 simulations⁴⁰.

The results from simulations with LDT “On” and “Off” are compared first. Subsequently, the focus of this chapter will shift to a comparison across auction mechanisms with LDT “On”. At this point, auction efficiency, surplus, and industry characteristics will be examined in more detail.

6.1 Auction Comparison by Type

In the next four sections, auction mechanisms will be compared type-by-type to determine the effects of Learning Direction Theory (LDT) on variance, price levels, and normality. The next section will describe the comparative procedures for the English auction with and without LDT. Subsequently, results from each of the sealed price auctions will be presented and discussed.

6.1.1 English Auction

Results from the English auction are presented here. I will compare and contrast the results of farmland transactions carried out via the modified English auction mechanism described in Chapter 3, both with and without LDT. Descriptive statistics are presented first and discussed, while statistical significance tests for differences between sample means and variances follow. Finally, I will present a graphical representation of average sale price per acre and the standard deviation of price.

Table 6.2 contains descriptive statics for the English auction with and without LDT. These statistics are based on the entire sample of data for each type of auction. Observe that the English auction with LDT On yielded 169,265 transactions, while the English auction without LDT resulted in 170,986 transactions. While small, this difference might be attributed to factors such as differences in initial random spatial distribution of farms, or the random order in which agents take turns performing actions. Nevertheless,

⁴⁰ Select simulations were run for 300 iterations of 35 years to ensure robustness. No significant differences were found. 100 iterations per simulation was chosen for data management reasons.

the difference represents only approximately 1% of total transactions and does not influence the overall results.

The average price per acre of land with LDT On was \$550.69, an amount equivalent to \$82,603.50 for the average plot of land in this simulation. Average price per acre and plot price with LDT Off are \$544.36 and \$81,654.00 respectively. A two-sample t-test⁴¹ assuming unequal variances was performed to test if the differences in means are statistically significant. Table 6.3 shows that the means are statistically different from one another at 5%, as are the variances (Table 6.4)⁴². Moreover, both samples have positive kurtosis, which implies a higher peak and fatter tails, where fat tails arise from relatively frequent extremes. So an English auction with LDT Off has slightly fatter tails and is less “normal” than an English auction with LDT On. Both samples are also positively skewed, which suggests that the mass of the distribution is concentrated to the left – the lower end of the price/acre distribution. Note also that both auctions generate bids that range from the mid \$200 range, to \$1000 per acre.

Table 6.2 Descriptive Statistics: English Auction with LDT On/Off

<i>English Auction</i>	<i>LDT On</i>	<i>LDT Off</i>
Mean	550.69	544.36
Median	549.15	542.89
Mode	551.25	551.25
Standard Deviation	71.42	69.19
Kurtosis	0.64	0.95
Skewness	0.26	0.29
Observations	169265	170986
Range	748.65	725.55
Minimum	255.15	270.90
Maximum	1003.80	996.45

⁴¹ See: Snedecor, George W. and Cochran, William G. (1989), *Statistical Methods, Eighth Edition*, Iowa State University Press.

⁴² A Mann Whitney U Test (non-parametric) was also used and showed that the data are normal and that differences are significant, further buttressing the results from the T and F-tests.

Table 6.3 Two Sample T-Test: Means of English Auction LDT On/Off

t-Test: Two-Sample Assuming Unequal Variances	
df	339654
t Stat	26.24
P(T<=t) two-tail	0
t Critical two-tail	1.96

Table 6.4 Two Sample F-Test: Variance of English Auction LDT On/Off

F-Test Two-Sample for Variances	LDF On	LDF Off
df	169264	170985
F	1.07	
P(F<=f) one-tail	0	
F Critical one-tail	1.01	

Figure 6.1 maps the evolution of average price per acre over the simulation period and includes the average standard deviation in each period across the 100 simulations.

Before this discussion, I would like to draw attention to the following point.

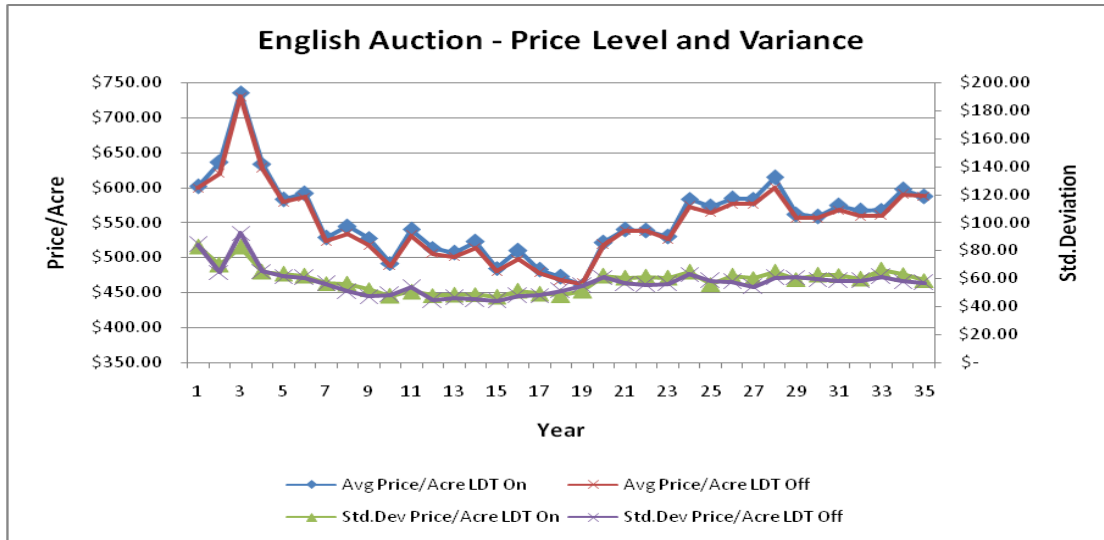
Recall that data for periods $t < 0$ are estimated *ex ante* and are exogenous to the simulation. On one hand, given the exogenous initialization data, it may be acceptable to analyze simulation data starting at $t = 0$. On the other hand, it may be more accurate to divide the data from Figure 6.1 into 2 groups. The first group of data would be the years 0 – 10. In this stage of the simulation the model is working partly endogenously, and partly from data inputted at $t = 0$. Keep in mind that it appears to take some time for the simulation to stabilize and start working fully endogenously. For this reason, it may be more appropriate to consider years 0 – 10 as an adjustment phase, and years $t > 10$ as the movement to steady state (if one exists).

It is impossible to know exactly when the simulation becomes completely endogenous. As a result, $t = 10$ was arbitrarily chosen. I offer that, assuming that much of the exogenous data from $t = 0$ has dissipated by $t = 10$ is a reasonable assumption because agents use past data that is no more than 5 periods old to determine expectations in the current period and they are limited with respect to price information memory⁴³. Early

⁴³ It is possible that data from $t = -5$ affect the results in $t = 34$. However, given the nature of the feedback mechanism and information diffusion it is impossible to know for certain. However, given the vast

data may tell us something about how changes in regime matter, while later years can tell us about the effects of different auction mechanisms occurring when the simulation is completely endogenized.

Figure 6.1 Price Level and Variance: English Auction LDT On/Off



To start, price/acre (LDT On/LDT Off) and standard deviations of prices (LDT On/LDT Off) track very closely together. This suggests that an English auction will perform similarly with and without learning using LDT. This result is likely attributable to the revelation of bids and the bidding structure in the English auction because values are affiliated. What is also clear from Figure 6.1 is that both price/acre and standard deviation of price/acre spike in the early stages of the simulation. This is likely a function of farm agents acting partly on learned information from both simulated and inputted data. But after 6 time periods, there is a fall in both price level and standard deviation. This is consistent with the assumption of limited agent “memory” and expectation formation assumptions. Observe that prices and standard deviations remain low until year 19, after which there is a slight increase in both variables. After year 19 prices tend to rise, while standard deviation remains more or less constant.

information flows in the model, any one observation is likely to have minimal impact after 11 time periods.

Trends in prices can be attributed to, at least in part, the assumed crop yields and crop prices. Cycling in prices and yields (and revenue) is expected to result in cycling in land prices. The degree of the cycling in land prices – and variance – may vary across auction mechanisms.

6.1.2 FPSB Auction

Results from the FPSB auctions with and without LDT are presented here. Recall that under this mechanism bidders have incentive to shave their bids based on the number of bidders in the auction, and that only winning bids are revealed.

In this auction, both price means are lower than the English auction and the variation in bids is almost half that of the English auction. But more important is the difference between the bids in the FPSB with LDT On and OFF. LDT Off generates bids that are on average almost \$32.00 less per acre than FPSB with LDT. There is also a greater difference in the standard deviation, over \$11.00/acre. Tables 6.6 and 6.7 show that there is a statistically significant difference in the means and variances at a 5% confidence level. Both distributions also have positive kurtosis and skewness. The numbers of observed transactions are also similar, to each other and to the English auction. Notice as well that the ranges of bids for both FPSB auctions are nearly half the range of the English auctions. This means that the extreme bids are much closer to the mass of the distribution under FPSB.

The average price/acre for an average plot of land under FPSB with LDT On is \$502.07, which translates to \$75,310.50 for an average plot of land. Without LDT, these prices are \$470.74 and \$70,611.00 respectively.

Trends in prices/acre and standard deviations of prices are found in Figure 6.2. The directions of the trends are similar to those found in the English auction: prices start out high, fall around year 6, and then begin to rise again in year 19.

Table 6.5 Descriptive Statistics: FPSB Auction with LDT On/Off

<i>FPSB Auction</i>	<i>LDT On</i>	<i>LDT Off</i>
Mean	502.07	470.74
Median	500.7	470.12
Mode	484	485
Standard Deviation	44.90	33.44
Kurtosis	0.40	0.29
Skewness	0.14	0.06
Observations	173494	173914
Range	470	341.68
Minimum	263	288.68
Maximum	733	630.36

Table 6.6 Two Sample T-Test: Means of FPSB Auction LDT On/Off

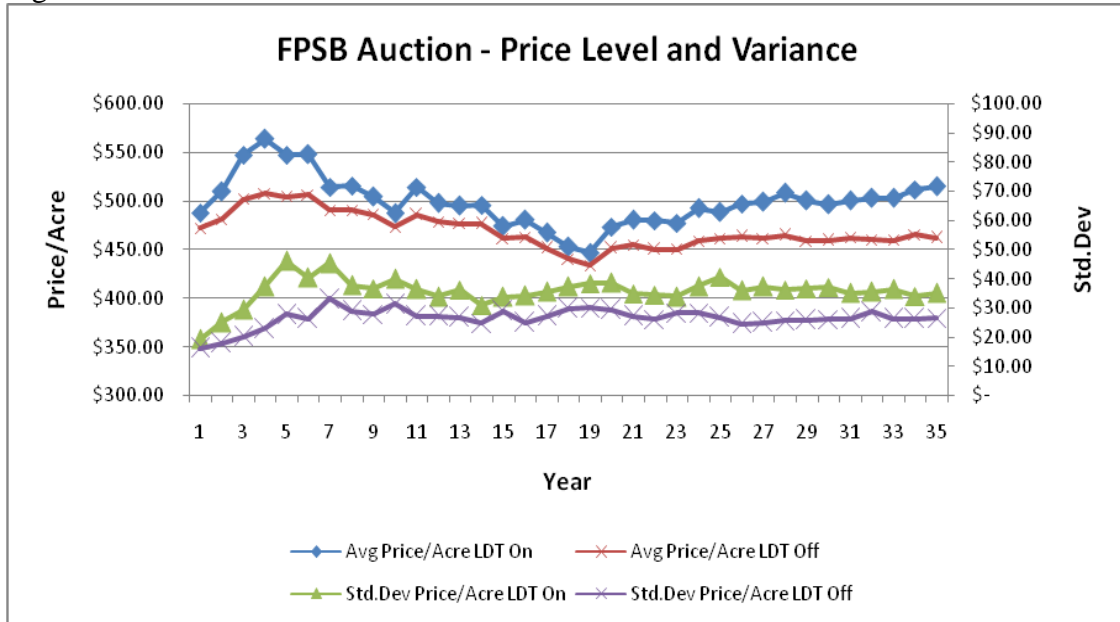
t-Test: Two-Sample Assuming Unequal Variances	
df	320652
t Stat	233.24
P(T<=t) two-tail	0
t Critical two-tail	1.94

Table 6.7 Two Sample F-Test: Variance of FPSB Auction LDT On/Off

F-Test Two-Sample for Variances	<i>LDT On</i>	<i>LDT Off</i>
df	173493	173913
F	1.80	
P(F<=f) one-tail	0	
F Critical one-tail	1.01	

However, the overall price level and variance are lower than under the English auction. More interesting is the gap between trends in price/acre and standard deviation between FPSB auctions with and without LDT. And while it was noted that the English auctions tracked rather closely with one another, this phenomenon is not observed in the FPSB auctions.

Figure 6.2 Price Level and Variance: FPSB Auction LDT On/Off



The FPSB auction with LDT On is everywhere greater than with LDT Off with respect to both price and standard deviation of price. This implies that LDT has a more profound effect on prices and its variance in the FPSB auction than in the English auction.

The sealed-bid auction decreased the variance and price level of land prices relative to the English auction. I suspect that the FPSB results in lower bids in the simulation than the English auction because farm agents have incentives to strategically undercut their true valuations to arrive at their optimal bid. Moreover, since bidding is single staged with no revealed bids, FPSB does not result in back and forth bidding between agents, as in the English auction, further driving up the price and the variance.

It is quite apparent that the FPSB follows the same general trends in prices as the English auction, as expected, but does not generate the same price level and variance. And the most distinct difference between auction mechanisms is the gap between trends when LDT is On and Off.

6.1.3 SPSB Auction

The next auction mechanism to be considered is the SPSB. As discussed earlier, it is a dominant strategy for farm agents to bid their true valuation in the SPSB since their valuation does not affect the final price paid. It should also be noted that under certain assumptions (i.e. private-values) the English auction and SPSB auction will generate similar results. Recall I assume that farm land possesses affiliated-values signals. To this extent, any differences in results from SPSB and the English auction may be attributed to, at least in part, the affiliated-values nature of farmland.

Descriptive statistics for SPSB simulations with and without LDT are listed in Table 6.8. Similar to the previous auctions, the SPSB auction with LDT yielded higher a mean price/acre and standard deviation. It should also be noted that the SPSB auctions produced the lowest means and variance (with respect to LDT choice) observed thus far. Average price/acre over the simulations were \$451.94 and \$421.94 with LDT On and Off respectively. This translates to final sale prices \$67,791.00 and \$63,291.00 for an average quarter section.

When compared against the English and FPSB auctions (accounting for the choice of LDT) the SPSB resulted in lower standard deviations of prices - \$39.76/acre and \$31.26/acre. This is a difference of \$8.50, which is less than the difference in standard deviations of the FPSB. Bids ranged from \$233-\$616 and \$222-\$582 per acre with LDT On/Off. Kurtosis was again positive for both auctions, while skewness was negative.

Significance tests for differences in means and variance tests again showed a significant difference between auctions. These results are shown in Tables 6.9 and 6.10.

Graphical representations of the results from the SPSB auctions are found in Figure 6.3. Upon first inspection it is evident that the SPSB auctions follow the same general trends as the previous two auctions; prices rise, then fall around year 6, and then rise again after year 19.

Table 6.8 Descriptive Statistics: SPSB Auction with LDT On/Off

<i>SPSB Auction</i>	<i>LDT On</i>	<i>LDT Off</i>
Mean	451.94	421.94
Median	455.83	424.09
Mode	446	421
Standard Deviation	39.76	31.26
Kurtosis	0.78	1.11
Skewness	-0.56	-0.56
Observations	172073	175246
Range	383	360.6
Minimum	233	222
Maximum	616	582.6

Table 6.9 Two Sample T-Test: Means of SPSB Auction LDT On/Off

<i>t-Test: Two-Sample Assuming Unequal Variances</i>	
df	326322
t Stat	246.93
P(T<=t) two-tail	0
t Critical two-tail	1.96

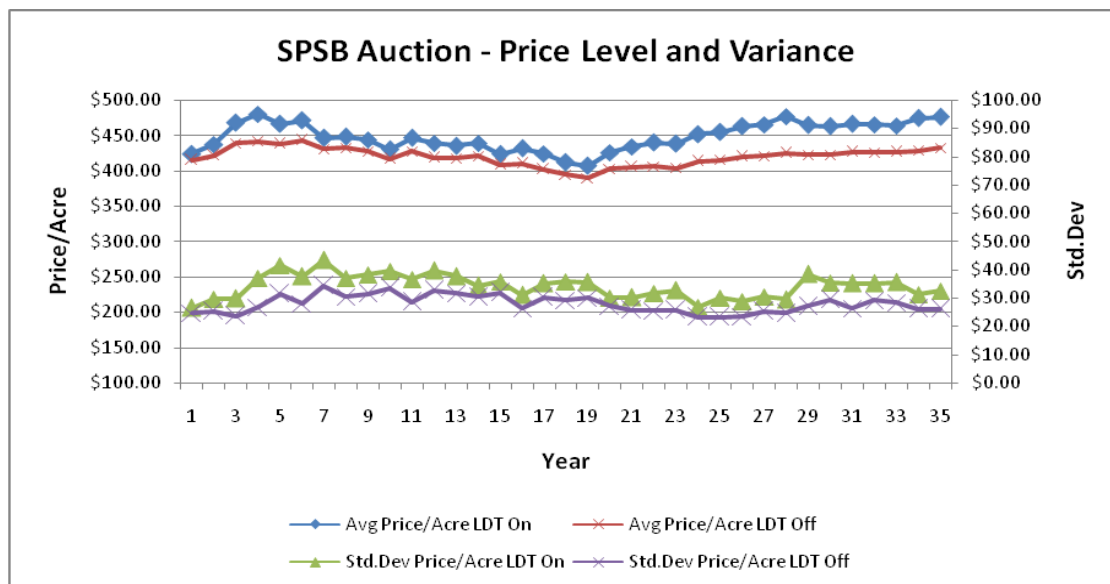
Table 6.10 Two Sample F-Test: Variance of SPSB Auction LDT On/Off

<i>F-Test Two-Sample for Variances</i>	<i>LDT On</i>	<i>LDT Off</i>
df	172072	175245
F	1.62	
P(F<=f) one-tail	0	
F Critical one-tail	1.01	

Also, note that prices and variance appear to track slightly closer with LDT On/Off than in the FPSB case, but not as close as the English auctions. Similar to the FPSB auctions, variance remains relatively constant after an initial increase in the first 6 years, even in the face of rising land prices in the last 15 years of the simulation. It also appears as though average price/acre diverges when prices are rising in general. I speculate that LDT magnifies the effects of upwards trends in prices and causes divergence when compared against the LDT Off case. Returning to the FPSB, it is obvious that the same is true.

The SPSB auctions also generate an average price/acre and standard deviation with LDT is On that is everywhere above the LDT Off case. Overall, lower price levels than comparative FPSB auctions can be explained if one considers the optimal bidding functions. Higher prices in the FPSB auction suggest thick markets where bids (and final prices) are very close to true valuation, whereas in the SPSB auctions agents always set bids equal to their true valuations, but with final prices that are systematically lower. Had the FPSB auctions been faced with thin markets, observed price levels may have been lower, and closer to those in the SPSB.

Figure 6.3 Price Level and Variance: SPSB Auction LDT On/Off



6.1.4 TPSB Auction

The final pair of auctions to be analyzed is the TPSB auctions with and without LDT. A first glance at the descriptive statistics reveals that the TPSB auction fits somewhere in between the SPSB and FPSB auctions with respect to price level and variance. Average price/acre with LDT On and Off are \$477.61 and \$465.15 respectively. Average sale prices are \$71,641.50 and \$69,772.50. Standard deviations vary only by \$5/acre (\$41.71 and \$36.29). Both auctions again have positive kurtosis and, similar to the SPSB, have negative skewness. Significance test for differences in the mean and variance are again statistically significant at 5% (Tables 6.12 and 6.13)

Table 6.11 Descriptive Statistics: TPSB Auction with LDT On/Off

<i>TPSB Auction</i>	<i>LDT On</i>	<i>LDT Off</i>
Mean	477.61	465.15
Median	480	467.11
Mode	471	459
Standard Deviation	41.72	36.29
Kurtosis	0.20	0.38
Skewness	-0.33	-0.43
Range	372.79	318.53
Minimum	260	267
Maximum	632.79	585.53

Table 6.12 Two Sample T-Test: Means of TPSB Auction LDT On/Off

<i>t-Test: Two-Sample Assuming Unequal Variances</i>	<i>LDT On</i>
df	341808
t Stat	94.07
P(T<=t) two-tail	0
t Critical two-tail	1.96

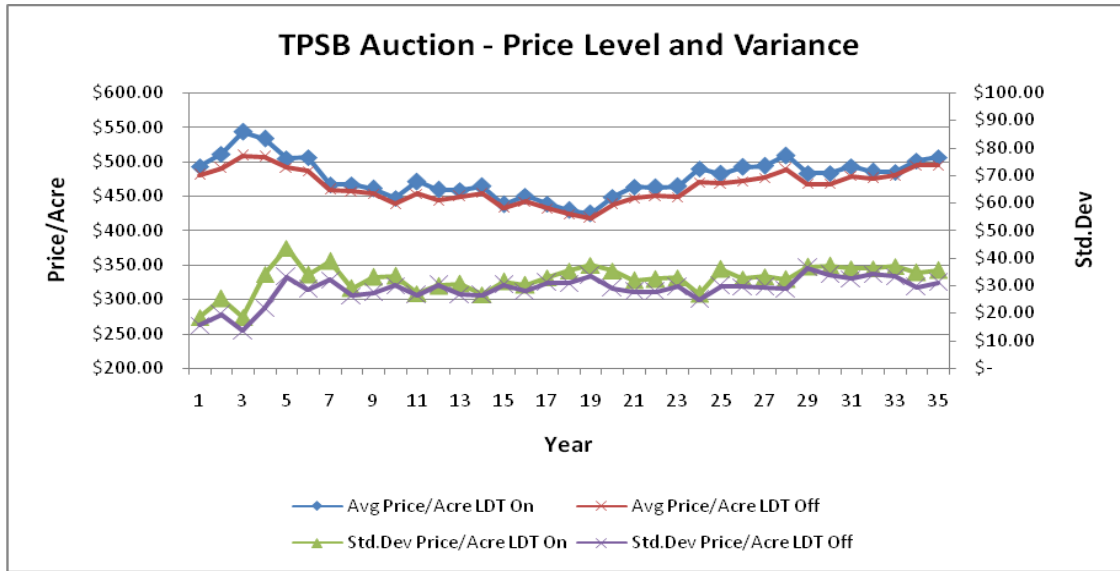
Table 6.13 Two Sample F-Test: Variance of TPSB Auction LDT On/Off

<i>F-Test Two-Sample for Variances</i>	<i>LDT On</i>	<i>LDT Off</i>
df	174014	174765
F	1.32	
P(F<=f) one-tail	0	
F Critical one-tail	1.01	

Finally, price level and variance for this auction are mapped in Figure 6.4. Results indicate that the general trend in price level is similar to the other auctions, further implying that overall *trends* in prices are driven not by choice of auction mechanism in the simulation, but instead by exogenous factors such as world prices and yields.

Clearly prices and variance with LDT On and Off track very closely in this case, perhaps the closest of all sealed-bid auctions. I conclude that the TPSB is the most robust sealed-bid auction when LDT is the assumed learning mechanism.

Figure 6.4 Price Level and Variance: TPSB Auction LDT On/Off



6.1.5 Overview of Results

The preceding discussion was aimed at comparing each of the auctions against itself with LDT On and Off. Some general results to be drawn include the following:

- 1) In each auction, LDT On resulted in a land price mean and variance that is statistically greater than the same auction without LDT. This is important because farm agents compete in a dynamic game and clearly LDT affects all of the auctions similarly⁴⁴.
- 2) All 4 auctions with LDT On can easily be ranked by mean price level and variance.
- 3) All auctions seemed to follow the same general trends in prices – trends that appear to be driven primarily by exogenous world prices and yields.

⁴⁴ The observant reader will notice that LDT caused increases in variance for all auctions. This result appears to go against intuition since one would assume that learning would cause a convergence in prices. I believe that my choice of learning mechanism led to these results. By definition LDT has a one period lag; therefore agents are abruptly modifying their bids upwards and downwards based only on the information from the previous period. Had there been several lagged variables, one might have witnessed adjustments that were less abrupt and more informed, drawing on a larger set of learning possibilities. LDT is likely not the most appropriate learning mechanism for this analysis. Further research should search for a more appropriate learning mechanism, or seek to improve on LDT.

4) With respect to the effects of LDT on prices/acre, the SPSB and FPSB seemed to react similarly, while the English and TPSB reacted similarly to each other, but differently than the SPSB and FPSB auctions.

6.2 Comparison of Auction Types with LDT “On”

The following section will focus on comparing auction mechanisms when LDT is On. Results with LDT Off will no longer be discussed because I assume agents are able to learn from repeated experiences and that the repeated nature of the game is of particular importance. It should be noted again that real world agents do not learn exactly by the LDT algorithm. Rather, LDT is an abstraction and was chosen for this analysis as a strategic learning framework partly for its simplicity and because relevant research found it to be a relatively good predictor of experimental behaviour (Neugebauer and Selten, 2006). In this light, one extension to this thesis would gather real bidding data from farmland auctions and use this to help determine the most appropriate learning theory to be employed in a simulated farmland auction.

The next four sections will focus on results from the simulated auctions with LDT On. Auctions will be compared on the basis of perceived surpluses, price levels and variance, and industry characteristics and evolution.

6.2.1 Perceived Surpluses and Total Surplus

This section will examine the perceived surpluses of both buyers and sellers in the simulated auction, as well as the total surplus generated by the auction mechanism. As stated earlier, the results of Harberger (1971) will be used to compare auctions on the basis of total surplus generated. For the remainder of this section, the terms surplus and perceived surplus will be used interchangeably.

Buyer surplus is estimated by subtracting the price paid for a plot of land from the upper bound facing the buyer; recall this upper bound can be the $\pi = 0$ constraint, or a borrowing constraint. Effectively, this becomes (WTP – price paid). Seller surplus is estimated by subtracting the plot’s reservation price from the final selling price, which is equal to (price-paid – WTA). Data presented here constitute the yearly average of all

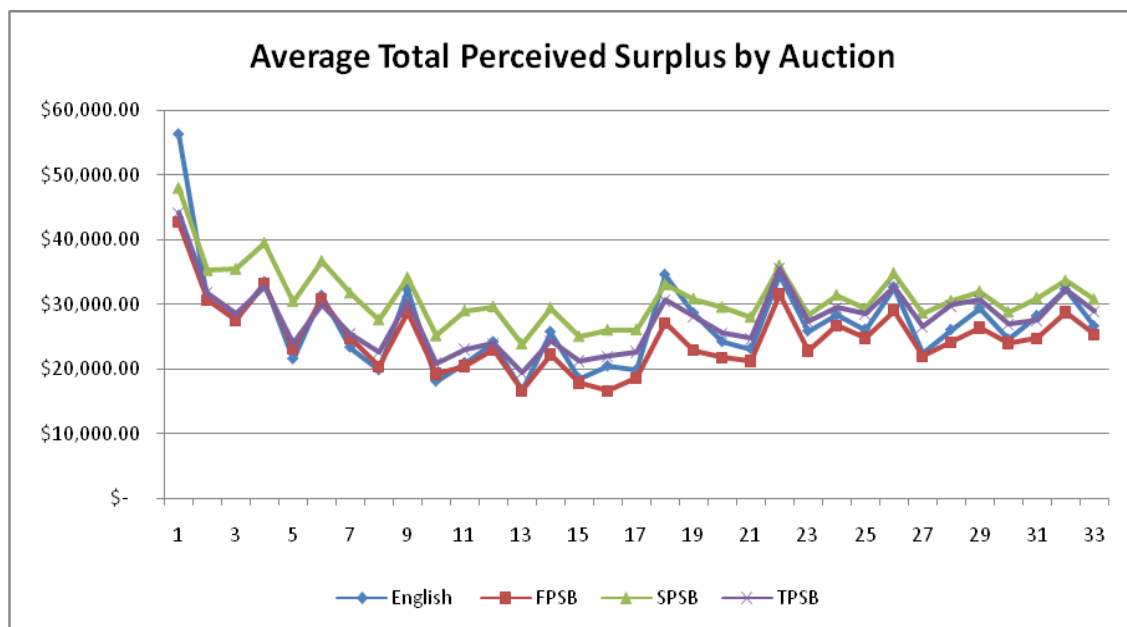
land transactions for all 100 iterations of the simulation and represents the average perceived surplus, either total or shared, from the sale of 1 average plot of land (i.e. cultivatable acres = 150 and quality = 1).

Figure 6.5 shows the average total perceived surplus generated by a transaction for an average plot of land. It is clear from figure 6.5 that all auction mechanisms follow a similar trend, beginning in the \$50,000/sale range, and finally stabilizing around \$25,000/sale. The same points made earlier about endogenizing the simulation model applies. If this is assumed to be the case here, we observe that after 10 years the simulations do level off and fluctuate about a mean that is in the vicinity of \$25,000 of surplus generated per sale.

Examining each auction mechanism independently, it is clear that after 10 years the SPSB auction generates the most total perceived surplus on average, followed by the TPSB auction, the English auction, and finally the FPSB auction.

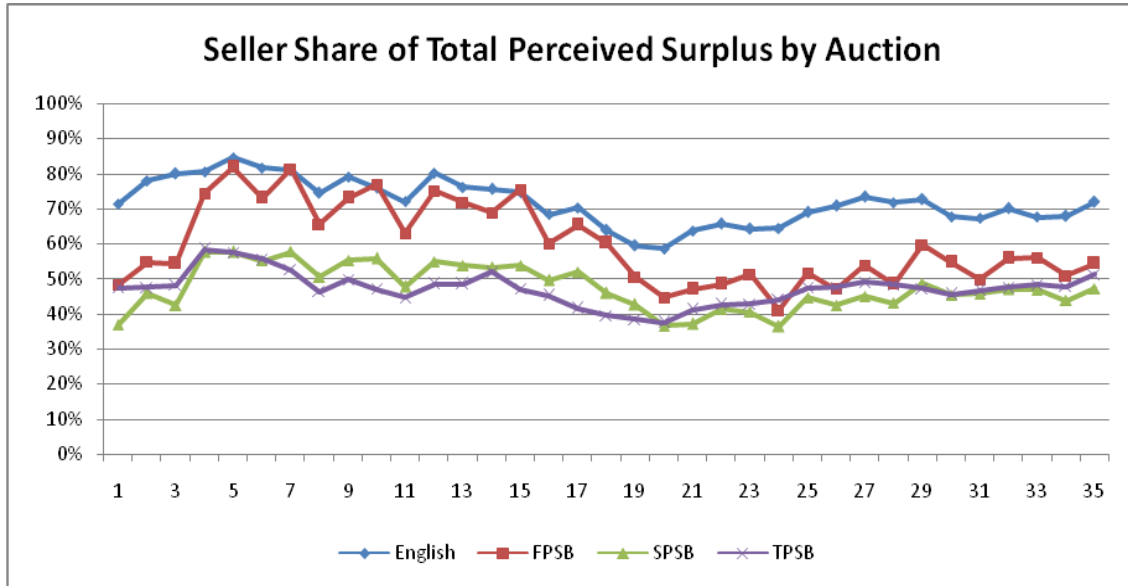
Based on grounds of distributional neutrality, I would suggest the SPSB auction because it generates the most total perceived surplus, followed by the TPSB, English, and FPSB auctions.

Figure 6.5 Average Total Surplus Generated from Sale by Auction



Shares of the seller's surplus are represented in figure 6.6. Seller share is simply the surplus received by the seller divided by the total surplus generated from the sale. Even after the simulations endogenize, it is clear that the English auction favours the seller. Sellers received, on average, 60-85% of the surplus from land sales with the English auction. Once again, I offer that this can be explained by the nature of the English auction and the affiliated-values assumption. Since the English auction allows all bidders to see all bids, and the auction unfolds over time, agents have a chance to increase their bids if they believe (based on observing other agents' bids) that they have under-valued the land. This means prices can be driven higher, even up to an agent's upper bound. As a result, this process yields more seller surplus.

Figure 6.6 Seller Share of Total Surplus from Sale by Auction



Note as well that the FPSB also generates systematically higher seller surpluses than the other sealed bid auctions. This can be explained by the effect of the number of bidders on the optimal bid. Recall that as the number of bidders increases in a FPSB auction, it is in a bidding agent's best interest to bid closer to their true valuation. This means that a thick auction will generate higher prices than a thin auction and, as such, it appears that in the first 20 years of a simulation the number of bidders is greater than in the last 15 years. This point will be re-visited in the concluding section.

Finally, the SPSB and TPSB auctions appear to generate the most equitable distribution of surplus between buyer and seller, with 35-60% of the surplus going to the seller. In later years, the seller's share of the surplus falls to 40-50%, meaning that in some cases the buyer gains relatively more from the transaction. As mentioned earlier, the basis for any discussion on distribution of surplus, or equity in these auction markets, is because future agricultural policy decisions may be influenced by the distribution of surplus from land transactions.

6.2.2 Farmland Pricing and Variability

This section will revisit the issues of farmland pricing and variability, but now I compare them across auction mechanisms. Average price levels over time are shown in figure 6.7. It is obvious that as time elapses, auction mechanisms can be readily ranked by price level from highest to lowest. The English auction tends to systematically generate the highest price, followed by the FPSB, the TPSB, and finally the SPSB.

Closer inspection reveals that as price levels trend downward they seem to converge; the greatest level of convergence occurs at year 19, which also generates the minimum average price for all auctions. After year 19, price levels rise and all auctions trend upwards. While the sealed-bid auctions appear to trend together, the English auction diverges from the sealed bid auctions. This suggests again that the English auction exaggerates price increases – attributable to the 2 stage bidding process and information feedback. Fundamentally, this occurrence is due to the strong affiliated-values nature of the English auction, and this auction may even generate systematic over-bidding in periods of increasing average price.

In standard auction theory, research has been done on increasing the efficiency of auction mechanisms. However, it is now known that when repeated bidding over time is coupled with an affiliated-values assumption, increasing auction efficiency (or even measuring it) can be very difficult. However, there is one commonly held belief in this literature: if values are affiliated (private + common), decreasing the variance of the bids decreases the variance of the common element, in turn increasing the certainty of the affiliated-value and increasing efficiency (Goeree and Offerman, 2002). To this

extent, measures of price variance are important for considering which auction mechanism has the potential to lead to the most efficient outcomes.

Figure 6.7 Average Price/Acre by Auction Type with LDT On

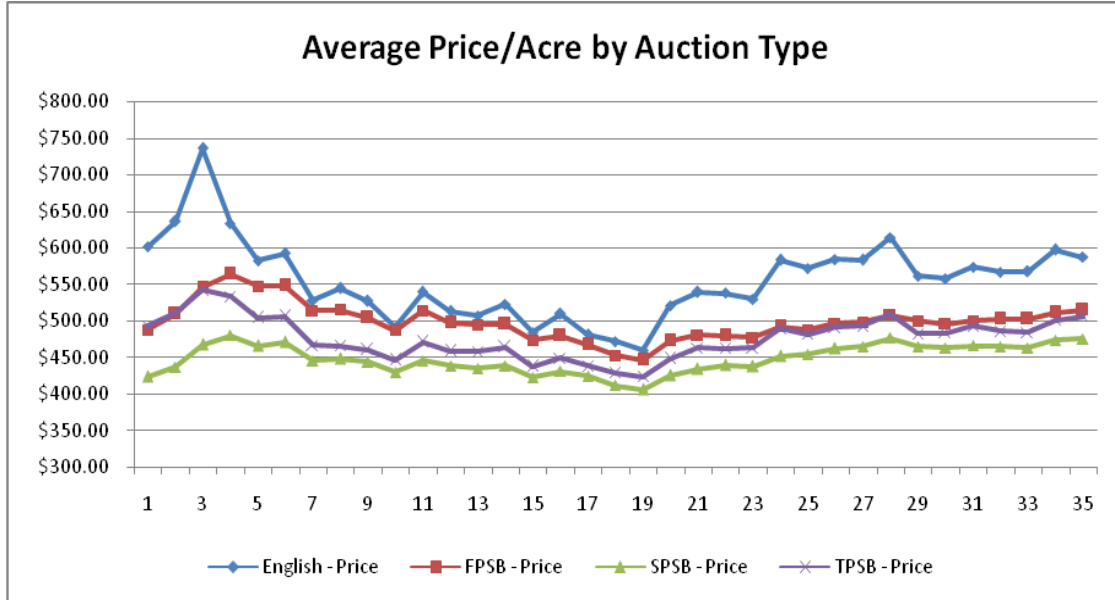


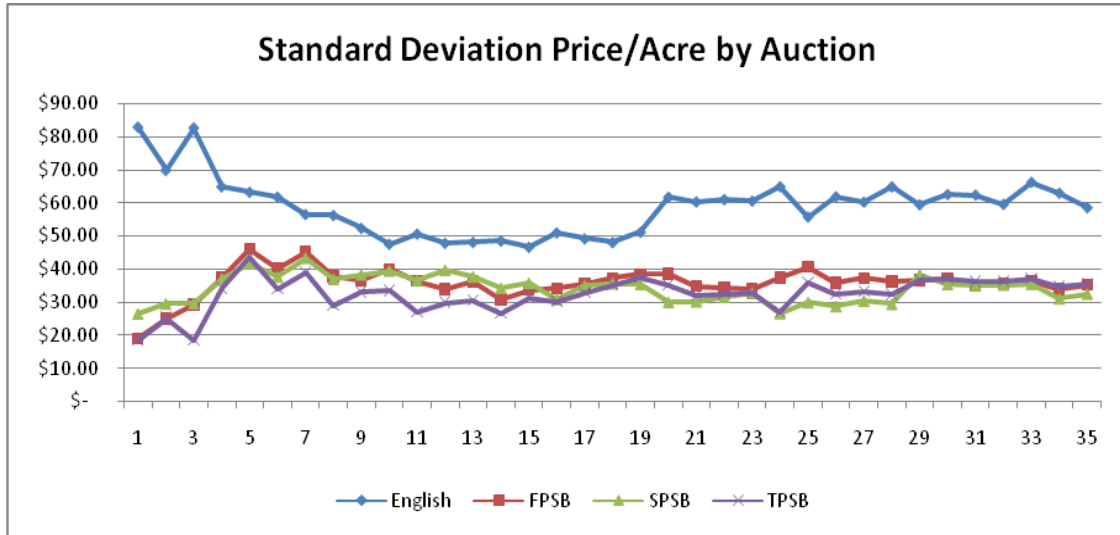
Figure 6.8 plots the average standard deviation of prices over time for all 4 auction mechanisms with LDT. The English auction generates the highest variance. This means that the common-value elements in the simulation have more uncertainty attached to them than the sealed bid mechanisms. Since I argued that increased uncertainty is harmful to market efficiency, the English auction is the least dynamically efficient auction among the tested mechanisms. Alternatively, it is difficult to say which of the sealed-bids auctions is the most efficient. The results show that in the later years of the simulation, all 3 sealed-bids auctions are equally efficient.

6.2.3 Industry Characteristics and Evolution

Until now, I have focused on the simulation results and the movement of prices, variance, auction surplus, and efficiency. However, I would like to consider the effects of auction choice on industry evolution. This final section will examine the effects of auction mechanism choice on agent participation in auctions, financial characteristics,

and on the evolution of market structure. More general conclusions will be drawn in Chapter 7.

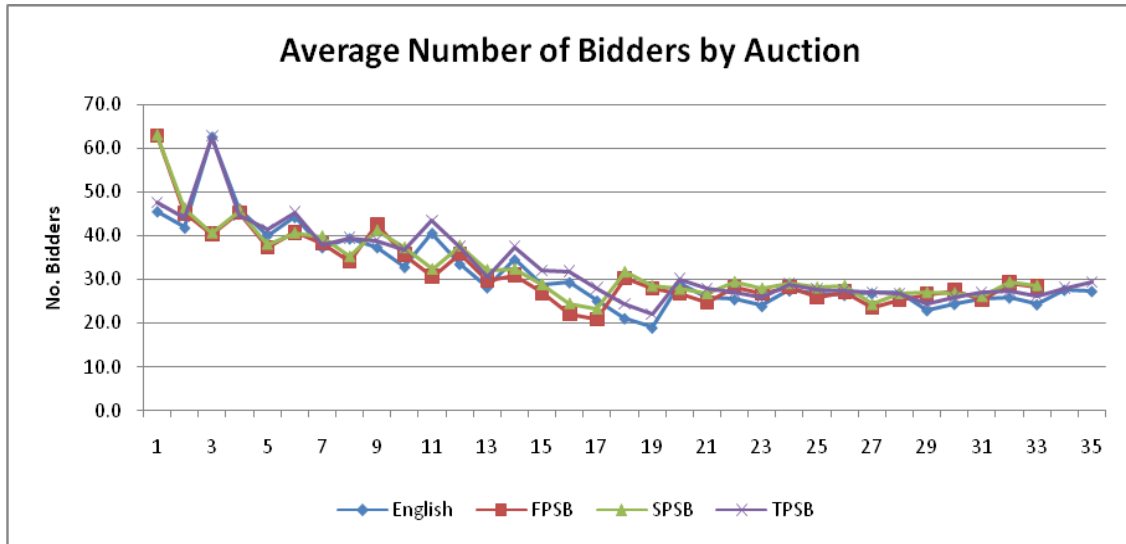
Figure 6.8 Average Standard Deviation of Price/Acre by Auction Type with LDT On



Market participation is simply defined as the number of bidders who participate in the bidding process. Recent experimental evidence suggests that the type of auction used will affect the number of participants drawn to the auction (Klemperer 2002). While the farm agents in this simulation are assumed to be indifferent *a priori* with respect to the type of auction used, it is possible that the choice of auction mechanism may interact with certain farm agent characteristics, in particular those that could exclude them from bidding (i.e. liquidity and solvency). If this were to occur, there may be significant differences in bids due to the assumed optimal bidding functions applicable to auction. Figure 6.9 shows the average number of bidders who took part in each auction over the simulation period for each of the auctions under LDT.

Observe that after year 5, there appears to be little difference between the number of bidders who participated in the auctions, regardless of choice. This is even more pronounced after year 19 when all auction mechanisms appear to generate, on average, between 25-30 bidders for each auction. This finding also reaffirms my discussion concerning the results shown in figure 6.6 and the dramatic change in surplus shares after year 19 when the auction mechanism is FPSB.

Figure 6.9 Average Number of Bidders per Auction by Auction Type



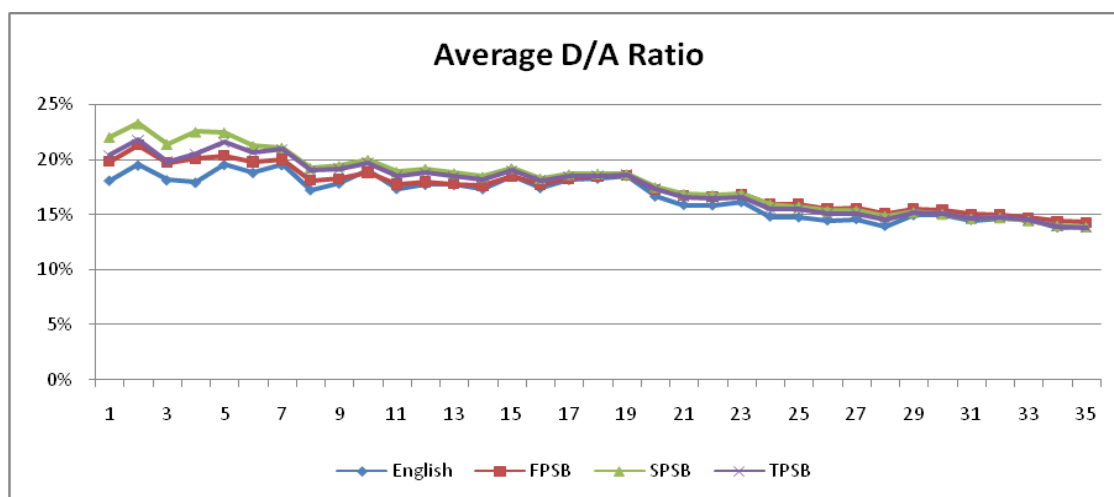
In light of figure 6.9, I conclude that auction specification does not affect bidder participation in this land market simulation. This is an important outcome worthy of further consideration (but outside the scope of this thesis) because in contrast, there have been several documented cases of market thinning as a result of auction choice and rule specification (Klemperer 2002).

The next issue to address is the role that auction choice may have on the financial health of the farm and agricultural industry. One of the most accepted measures of financial health is the debt to asset ratio (D/A Ratio). Figure 6.10 shows the evolution of the average D/A ratio of remaining farmers in each of the simulated auctions. The same general pattern of convergence seen in figure 6.9 is apparent, where differences in the early years are likely caused by assumed average prices of land for years $t < 0$. The only other slight divergence visible in the diagram occurs for the English auction in years 20 – 28. I suspect this is due to the abrupt increase in land prices in the simulation (see figure 6.7) and the resulting higher level of debt that land buyers had to carry.

Although initially somewhat unexpected, the data generated in figure 6.10 ultimately make intuitive sense. Debt is an amount that must be borrowed to invest in land and other capital items. Here, the level of borrowing is directly affected by the price paid for land, and the average market price of land determines the asset value of land. In

effect, increasing (decreasing) land prices leads to increasing (decreasing) debt levels so long as the increases (decreases) are moderate in nature. Figure 6.11 might look significantly different if there were other abrupt and significant changes in land prices, such as those in the English auction years 20 – 28⁴⁵.

Figure 6.10 Average D/A Ratio by Auction Type

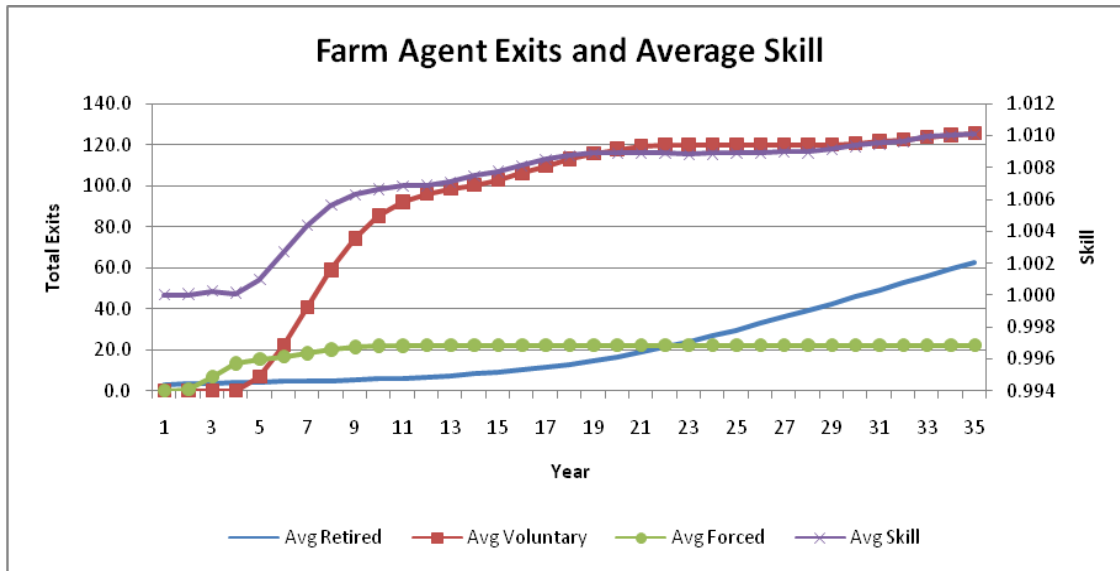


Finally, farm agent exits and average farm size are graphed in figures 6.11 and 6.12. The data in figure 6.11 are from simulations under the English auction only. The results from sealed-bid auctions are not presented for graphical simplicity, and because there is no discernable difference between auction specifications. The graph shows the total number of exits by type, and the average skill level of remaining farmers.

The number of retired exits steadily increases as farmers age. The number of forced exits (insolvency) begins and ends between years 3 and 9. On average, 20 farm agents (4.7%) are forced out of the industry, all in the early stages of the simulation. The largest type of exit is the voluntary exit (equity protection). In sum, over 35 years of simulation, a total of 120 (28.4%) farmers voluntarily exit the industry, most of whom do so through years 5 – 11.

⁴⁵ The overall decreasing trend may be a result of aging farmers, slowly paying off their debt and not purchasing any more land. However, the fact that all auctions trend similarly is of interest, not necessarily the trend itself.

Figure 6.11 Farm Exits and Average Skill of Farm Agents (English Auction)⁴⁶



Recalling the conditions for voluntary exit, this result implies that from year 1 approximately 100 (23.7%) farmers are faced with $NCFBI < 0$ for 5 – 9 consecutive years. The cause of the exits can be explained, at least in part, by average skill. It is clear that in this simulation, as farmers voluntarily exit, average skill increases. This means that the majority of farmers voluntarily exiting have average skill < 1 as expected. Without income support, these below average skilled farmers do not stay in the market for equity protection purposes⁴⁷.

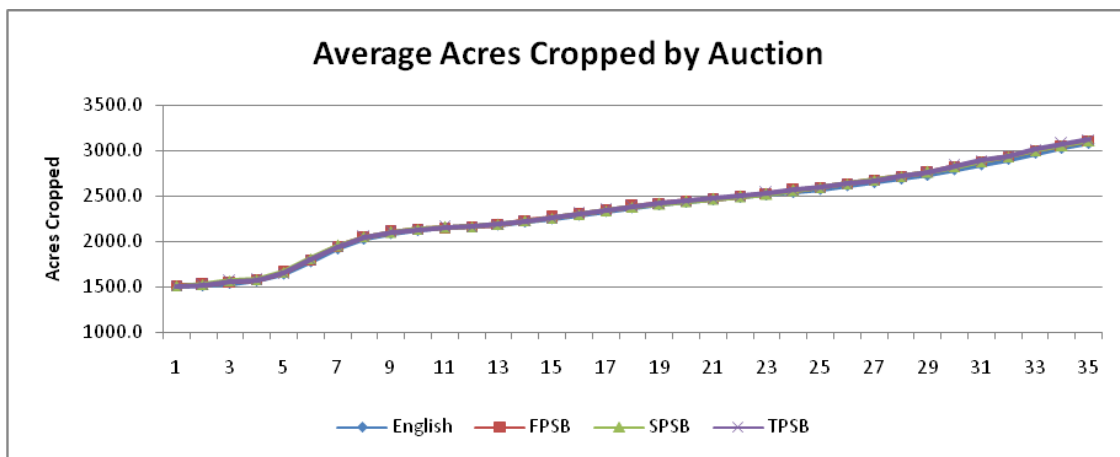
Figure 6.11 also shows that, on average, there are between 200 and 210 exits per simulation, representing 50% of the initial population. In effect, I would expect that average farm size would double over the duration of the simulation, as it does. And figure 6.12 shows that regardless of auction choice, average farm size evolves at the same rate.

⁴⁶ Other auctions are omitted from Fig. 6.11 for graphical simplicity and because they do not differ from the results obtained via English auction. Sealed-bid auction data are available upon request.

⁴⁷ It should be noted that this type of behaviour is not observed in actual markets for a number of reasons. Firstly, agents are not hyper-rational with respect to equity protection and may remain in the market even if $NCFBI < 0$. Secondly, producer supports often mitigate the effects of $NCFBI < 0$ and allow marginal farmers to remain in the market. Thirdly, there is an element of luck that is coupled with skill to determine farmer revenue - this is not explored here. Lastly, the simulation is without exogenous shocks (border closings, new policies). Such shocks change the evolutionary path, causing one-time mass exits or more favourable conditions for marginal farmers. Removing the effects of such shocks is difficult and the “natural” exit trend is forever changed.

Overall, my results strongly suggest that, under the given assumptions, choice of land auction mechanism has almost no effect on agricultural market structure, farm financial characteristics, or farm agent characteristics. This is a strong conclusion resting upon some strict assumptions, but the choice of auction mechanism has little effect on the macroeconomic characteristics of this industry in these simulations. This stands in contrast to other primary results where I found that auction specification does play a large role in pricing efficiency and surplus allocation⁴⁸.

Figure 6.12 Average Total Acres Cropped by Auction



6.2.4 Overview of Results

A comparison of outcomes across auctions with LDT On were presented and examined in this section. To summarize:

- 1) The SPSB generated the most perceived total surplus, followed by the TPSB, English, and FPSB auctions respectively.
- 2) The SPSB and TPSB resulted in the most egalitarian distribution of surplus between the buyer and seller. While potentially important for policy analysis, I draw no conclusions about an “optimal” distribution of surplus in this land auction environment.

⁴⁸ It is also worth noting that the average distance between farmland and the farmstead decreased by approximately 25% during the course of the simulation. This result is similar for all auctions and LDT choices. It suggests that farmers try to purchase land close to the farmstead so as to minimize costs.

3) The English auction generated the most variability in prices. All the sealed-bid auctions performed equally well. This suggests that the common-value elements of the bids in an English auction generates higher price variability than the common-value elements in the sealed-bid auctions.

4) The English auction generated, on average, the highest prices. This was followed by the FPSB, TPSB, and SPSB auctions respectively. The English auction also exaggerated upward trends in sales price more than the sealed-bid auctions.

5) Contrary to my prior expectations, auction choice had no effect on aggregate market characteristics or industry evolution.

6.3 Summary

I described the results of eight simulations of farmland market auctions, each with 100 iterations of 35 years. The results generated support certain aspects of existing theory, yet they also offer some insight into additional areas yet to be explored. All my findings suggest that auction or mechanism design has no effect on industry level indicators – the path is different for different auctions, but the final outcome is virtually the same for all auctions. Chapter 7 will examine these results and discuss them further with agricultural policies in mind.

CHAPTER 7

CONCLUSION

7.0 Introduction

This section will briefly review and summarize the results of this thesis. The limitations of MAS modeling will also be discussed within the context of farmland auction markets. Some general conclusions about farmland auction markets are made, staying mindful of the results and the limitations of the model. The chapter will conclude with suggestions for future research.

7.1 Summary of Results

7.1.1 Learning Direction Theory

Section 6.1 compared auctions of the same type with and without the imposition of a modern theoretically based individual learning scheme: LDT. All four auction types were found to generate greater means and variances when LDT was present. Differences between the means and variances were significant at a 5% level of significance. This result concurs with the work of Neugebauer and Selten (2006) who found that LDT explained, at least in part, some of the over-bidding phenomena observed in repeated auction experiments. As discussed in this thesis, my findings may run against intuition about the expected effect of a learning mechanism (increased variance), but I argue that LDT is not so much a true learning mechanism as it is a bid adjustment theory. In effect, to be a realistic learning mechanism (i.e. one that would decrease variance), LDT must be improved upon.

Nevertheless, these findings are important because much of the research about land prices assumes that they are either influenced by speculation, hedonic pricing, capitalization, or expected revenue (Huang et al. 2006). My results suggest that a

portion of land prices in modern agriculture could be attributed to a strategic bidding component, where a strategic bidding component is a factor in price formation when there is repeated play. This is an aspect of land markets that is often overlooked in current analysis.

Although LDT had a measurable effect on all auctions, it did not affect all auctions equally. For instance, I observed that LDT had a more noticeable effect on the SPSB and FPSB auctions than on the English and TPSB auctions. I cannot say exactly why this occurred. I speculate that it may be a consequence of the assumed bidding functions. In both the English and TPSB auctions, bids are generally equal to, or above⁴⁹, an agent's valuation, meaning that there is less room for agents to ratchet up their bid using LDT because they are bounded by credit or profitability constraints. Whatever the exact reasons, it appears as though the English and TPSB auctions are more robust to LDT.

7.1.2 Auction Performance

One goal of this thesis was to better understand the effects of learning, information diffusion, space, and time in a repeated farmland auction setting. As a result, auction performance measures were applied to simulations with LDT On.

The simulation results showed that price level was highest when an English auction was used, and lowest under the SPSB. This supports the work of Milgrom and Weber (1982) who use an affiliated-values model to explain the divergence from the traditional *private-values revenue equivalence theory* results. While this thesis in no way seeks to uncover an “optimal” price level, standard farmland research in agriculture is concerned about such issues.

Concerns about optimal farmland prices arise because “overpriced” farmland can lead to financial weakness as well as divert funds from areas with higher returns on investment. Alternatively, “underpriced” farmland may cause some land to gravitate

⁴⁹ Recall that in a TPSB the optimal bid decreases the in the number of bidders to the true value, and that in the English auction bidders can re-evaluate their bids once they have gathered information, and bid higher in the second round.

away from its highest and best use and away from the most efficient producers. In light of this, auction choice and price levels are important for agricultural policy considerations.

Farmland price variance was greatest under the English auction, implying that the English auction may be the least efficient mechanism for land markets. The sealed-bid auctions examined here all performed equally well under this efficiency criteria, implying that uncertainty in common-values might be reduced with the use of sealed-bid auctions when farmland values are assumed to be affiliated in nature.

I conclude that if it was in the interest of agricultural policy makers to reduce the overall variance (and increase market efficiency) of sale prices in the agricultural land market using auctions, I would suggest a sealed-bid auction.

Conversely, the English auction was found to exacerbate upward trends in prices relative to the sealed-bid auctions. This effect is attributable to the presence of revealed bids coupled with the affiliated-values assumption. In turn, this suggests in times of rising land prices, the use of an English auction would contribute to increasing prices and could lead to over bidding.

Under the assumptions made in this simulation, the SPSB was found to generate the most total perceived surplus of any auction, rendering it the most efficient auction mechanism considering Harberger's (1971) postulates. Furthermore, the SPSB resulted in the most equitable split in surplus between buyer and seller (followed closely by the TPSB). If total perceived surplus and equal share of surplus in land auctions is a concern for agricultural policy, it would be in the best interest of policy makers to adopt the SPSB auction as the standard.

Although no "one-size-fits-all" conclusion about auction choice can (or should) be made based on the results generated here, from a sustainable policy standpoint it appears as though the SPSB auction is the best choice. That is to say that in the context of this highly stylized simulation model, the SPSB auction outperforms all other auctions in that it generates the most surplus, yields an even share of surplus, as well as

low transaction prices and low standard deviations of prices – all of which are factors that in the long-run would work to stabilize the economic health of real land market and the farming industry.

7.1.3 Market Characteristics

The results of section 6.2.3 demonstrated clearly that the choice of auction design had little impact on market structure. While unexpected, this cannot be classified as emergent behaviour because upon closer inspection it appears that some of the assumptions made within the model likely contributed to this result (Tesfatsion 2002)⁵⁰.

I originally posited based on auction theory that mechanism design would affect prices (both levels and variance) as well as the quality of information. From this, it was believed that industry as a whole (the system) would evolve in a way that reflected the results of each type of auction. In addition, I originally speculated that higher prices and variance would lead to more market instability, leading to more exits and fewer active bidders than an auction that generated lower, more stable prices. However, this set of circumstances was not verified by my simulations.

The fact that each of the four auctions systems evolved almost identically can be explained not by a single, but a number of factors. Each of these factors worked to nudge the industry along its path, despite the choice of auction design and the effect this had on prices and information. To begin to explain this result, I must go back to some key elements upon which this thesis was built. These are capital assets, income generating incentives, and optimal bids.

Consider for a moment the nature of the land market. A farmland auction market is based on the underlying assumption that farmland is purchased to generate income and accumulate equity. This is in stark contrast to some markets for private-value goods, where often times the price paid for the good is a function of its private-value alone and there is no consideration for re-sale value or income generating ability.

⁵⁰ It should be noted that the certainty of this conclusion cannot be known until more research is carried out.

Agents who are concerned about the income stream of a capital asset are necessarily limited to transact at either the WTA or WTP for the good. As such, there are natural upper and lower bounds on these prices – unlike auctions for unique pieces of art. Moreover, income/productivity incentives signal agents to expand, or exit the industry and thus dictate the need for a market mechanism to sell farmland.

The simulations showed that regardless of auction type, there are agents who are willing to exit the market and sell their land, and there are those who are willing to purchase land. Therefore, one could say that the path of the market is dependent on the rationality of agents in terms of income generating opportunity and equity protection.

The natural upper and lower bounds on the price farmland, coupled with the fact that farm agents are (or should be) income/productivity driven causes the market to track in the same direction in the absence of exogenous shocks and in spite of auction choice. Thus, I conclude that the natural path of the model is driven by farm agents, a.k.a. *homo economicus*, and their desire to generate income. Ultimately, my findings imply that so long as the mechanism of choice supports income generating incentives, the system is robust to auction or mechanism design⁵¹.

Finally, the assumed bidding strategies probably played an important role in the evolutionary paths of the simulations. Recall that for tractability, optimal bidding functions were assumed to be equal for all agents *ceteris paribus*. As a result, all agents bid in exactly the same manner as all other agents in the simulation. In retrospect, this assumption led to a degree of heterogeneity in bidding that may have been sufficient to suppress any phenomena that might be considered emergent. In light of the lessons learned here, it would be interesting to examine the effects of including a more realistic learning process (for instance, via a genetic algorithm) within the optimal bidding

⁵¹ It should be noted that this stylized model does not allow for extreme deviations in prices due to the number of assumptions that are imposed. Real world markets however, may not operate as expected, and the effects of extreme deviations in prices and bids is still unknown in repeated games with information diffusion and learning. Allowing for exogenous shocks to the industry may result in shocks to land markets, changing the steady state path. In this case, using the most robust, efficient auction would be central to assuring that land markets do not crash or fluctuate out of control.

scheme. Future research could test to what degree truly heterogeneous bidding functions affect the results.

Although macro level indicators in the simulation remained relatively unchanged, this result does not imply that auction choice does not matter. I find that auction choice clearly has an impact on the final price paid, the variance of those prices, and total surplus generated. Reducing variance and ensuring the stable function of land markets goes a long way to ensuring that the information passed is of good quality, and that market power is minimized.

7.1.4 General Results

The simulations analyzed here generated certain results that buttress aspects of auction theory, e.g. the effects of learning, affiliated-values and overbidding. In this sense, my MAS simulations reaffirmed analytics. However, what was not expected was the impact, or lack thereof, of auction design on industry structure and evolution.

The nature of the complex system modeled in this thesis means that analytics could not have been used to formally solve it due to the presence of dynamic games and individual feedback. As such, the results from this model must be seen as supporting the theory as well as providing insights into land market evolution with feedback and a repeated game setting.

My results indicate that, in the absence of exogenous shocks, all auctions considered in the simulation appeared to be relatively robust in nature, ultimately resulting in the same land structure at simulation's end. The fact that all auctions produced a similar land structure suggests that even when bids are *sub-optimal*, well designed auctions can elicit good outcomes and nudge an industry in a competitive direction provided that the mechanism supports income generating incentives.

Although I draw no conclusions about which auction is *best* as a *one-size-fits-all* design, my findings indicate that a SPSB auction, designed correctly, can mitigate overbidding in repeated games, provide an equitable distribution of surplus, generate the greatest surplus, and send good quality signals about prices when the good to be

auctioned displays similar characteristics to farmland. But as always, these findings must be interpreted with caution since there are documented cases where SPSB auctions, coupled with thin markets, resulted in market failures by facilitating collusion and low seller surplus due to lower than predicted transaction prices (Kemplerer 2002).

7.2 Limitations of the Model

While MAS and other agent-based simulation methods have garnered a large amount of attention recently for ushering in a novel way to do economic simulation, it would be irresponsible to assume that agent-based methods are without flaws.

For instance, although extremely flexible, agent-based methods lead to debate about which factors to include in a model. The simulation described in this thesis is based on a set of assumptions about preferences, behaviours, and expectations that were ultimately used to make the model tractable, both in development and analysis of the results. As noted by Freeman (2005), researchers who perform this type of modelling are faced with a decision between including many realistic elements of the real-world against making some simplifying assumptions for the sake of tractability. Agent-based models have the flexibility to let the researcher decide what is, and is not, important. As such, researchers are sometimes faced with the daunting task of excluding certain elements of the model so that emphasis can be placed on others. The current literature on agent-based methods offers little guidance about how to make these decisions; one exception is Gilbert and Terna (1999).

I also made various assumptions about agents, their behaviours, and their local environment. Most notable however, were my assumptions about agents' optimal bidding functions and the learning mechanism. It is important to note that the assumed bidding schemes and learning mechanism were based on theoretical work, and by no means are guaranteed to capture authentic behaviour. They are approximations, as developed in the literature, and served to approximate as closely as possible real-world behaviour. It will take some time to develop a model (even in an MAS framework) that mimics actual bidding schemes and learning mechanisms since there is clearly still much to be learned about these processes.

The purpose of this section is not to question all assumptions, or highlight the limitations of the model. This section should be considered a disclaimer. All of the results discussed in this thesis need to be viewed in light of the limitations of MAS. The data generated from the MAS result from agents acting on the assumptions imposed on them. Although some of these assumptions may not be sufficient to imitate real world behaviours, the flows of information, evolution of time, and the agent landscape have offered valuable insights about farmland auction markets that were not available before MAS.

7.3 Suggestions for Future Work

This simulation model should be considered the basis for what could be a series of projects examining the effects of learning, feedback, space, time, and repeated games. There are a number of interesting extensions to this thesis. These include; 1) the inclusion of exogenous shocks to the industry to examine the performance of auction types; 2) experimenting with different types of learning mechanisms or ameliorating LDT; 3) including a lease market and linking it to the sales market through the flow of information; 4) experimenting with adaptive bidding behaviour, where bidders can alter their optimal bid based on experience, and, 5) modelling other markets (e.g. pollution credits) to measure auction performance when strategies and incentives change.

The extensions suggested would surely go a long way towards explaining observed bidding behaviour that cannot be explained using traditional equilibrium models. Furthermore, modeling auction markets using MAS has been shown to be extremely useful for enriching the literature when agents are endowed with characteristics similar to their real world counterparts, rather than the hyper rational economic agents that are typically assumed.

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APPENDIX A

Crop Prices and Yields Years $t = -5$ to $t = 34$

	Price	Yield	Price/Acre		Price	Yield	Price/Acre
Year	\$/Ton	Tons/Acre	\$/Acre	Year	\$/Ton	Tons/Acre	\$/Acre
-5	\$224.84	0.64695	\$145.46	16	\$224.01	0.60725	\$136.03
-4	\$216.84	0.7144	\$154.91	17	\$217.04	0.670365	\$145.50
-3	\$223.73	0.64885	\$145.16	18	\$207.70	0.696598	\$144.68
-2	\$218.06	0.61465	\$134.03	19	\$214.25	0.765343	\$163.97
-1	\$225.26	0.69825	\$157.29	20	\$217.80	0.686854	\$149.60
0	\$226.88	0.640594	\$145.34	21	\$218.56	0.649943	\$142.05
1	\$209.79	0.67925	\$142.50	22	\$213.88	0.664478	\$142.12
2	\$212.31	0.775882	\$164.73	23	\$218.10	0.765473	\$166.95
3	\$214.88	0.60093	\$129.12	24	\$213.84	0.67051	\$143.38
4	\$214.67	0.650015	\$139.54	25	\$197.30	0.781674	\$154.23
5	\$216.84	0.713726	\$154.76	26	\$220.65	0.649113	\$143.23
6	\$209.30	0.65892	\$137.91	27	\$217.37	0.726529	\$157.93
7	\$208.89	0.775433	\$161.98	28	\$216.34	0.637302	\$137.87
8	\$213.12	0.634687	\$135.26	29	\$217.26	0.694655	\$150.92
9	\$207.48	0.656224	\$136.15	30	\$208.82	0.746869	\$155.96
10	\$218.06	0.732204	\$159.66	31	\$209.63	0.691021	\$144.86
11	\$213.89	0.632296	\$135.24	32	\$217.07	0.703168	\$152.64
12	\$215.36	0.694461	\$149.56	33	\$228.17	0.691765	\$157.84
13	\$230.71	0.634266	\$146.33	34	\$218.03	0.669873	\$146.05
14	\$218.89	0.610859	\$133.71				
15	\$222.68	0.711077	\$158.34	MEAN	\$216.46	0.682318	\$147.57
				STD.DEV	\$6.47	0.05	\$9.71

Source: Author's Calculations based on data from Saskatchewan Agriculture, Food and Rural Revitalization 1985-2004

APPENDIX B

Simulation Code

Netlogo© version 3.1.3

Center for Connected Learning and Computer-Based Modeling in the Department of
Computer Science at Northwestern University in Evanston, Illinois
<http://ccl.northwestern.edu/netlogo/>

```
globals
[
simulation
plots-for-sale          ;; counts number of plots set up for sale each year
total-plots-sold        ;; counts number of plots that actually sold in that year
total-plots-unsold
plots-unsold-this-tick
reservation-not-met
plots-sold-this-tick
land-price
price-crop
yield-crop
year
tot-vc-prodn
avg-vc-prodn
tot-prodn-crop
avg-prodn-crop
tot-crop-revenue
avg-crop-revenue
avg-cost-prodn
tot-cost-prodn
current-plot-bid-on
current-list-of-bids
current-winning-bid
current-winner
price-paid
highest-bid
second-highest-bid
adj-winning-bid
list-of-winning-bids-adj
all-prices
auction-winner
auction-seller
auction-plot-acres
auction-plot-quality
auction-plot-location   ;; xcor ycor for easy calculation of distance to bidders farmsteads'
past-crop-prices        ;; array of past crop prices, most recent first
past-crop-yields        ;; array of past crop yields, most recent first
xloc
yloc
bidders
land-for-sale?
dead
retired-exit
voluntary-exit
forced-exit
credit-constrained
]
```

turtles-own	
[
age	
generation	
risk-aversion	
urgency	
skill	
attitude	
years-retired	
average-multiplier	
average-soil-quality	
buyer?	
exit	
type-of-exit	;;; 0 = no exit, 1 = retirement, 2 = voluntary, 3 = forced
plots-owned	
plot-for-sale	
plots-sold	
plots-purchased	
land-value	
capital-value	
asset-value	
equity-value	
debt	;;; current debt remaining at year end
cash	
NCFBI	;;; crop-revenue - tc-prodn - debt-payment-amount - family-
withdrawal	
list-NCFBI	
years-paid-debt	
principal	;;; current at year end (refers to last starting principal amount after a
purchase)	
debt-payment-amount	;;; payment that is due at the end of next harvest (at year end this refers to
coming year)	
principal-paid	;;; amount of principal paid to date (at year end this refers to yr that
just ended)	
capital-purchases	
expected-production-volume	
residual-to-land-labor	
residual-to-land-labor-exp	
acres-total-crop	
prodn-crop	
crop-revenue	
tc-prodn	
variable-prodn-costs	
hired-labour	
travel-cost	
trucking-cost	
family-withdrawal	
capital-replacement-charge	
;avgall-adj-prodn-volume	
years-neg-ncfbi	
years-neg-cash	
credit-constrained?	
active-bidder?	
times-bid	
winning?	
winner?	
won-last	;;; 0 = na, 1 = true, 2 = false
winning-bids	
expected-price	;;; expected price based on 3 yr weighted moving average of past crop
prices	
expected-yield	;;; expected yield based on 3 yr weighted moving average of past crop
yields	

expected-price-per-acre-adj
 distance-to-plot-bid-on
 expected-variable-prodn-costs
 expected-hired-labour-cost
 expected-transport-cost
 expected-capital-replacement-charge
 expected-netrev-per-acre
 initial-capital-investment
 expected-gross-rev
 expected-net-revenue
 expected-salvage-value
 annuity
 local-price-info
 global-price-info
 max-bid-per-acre
 max-bid
 max-bid-credit-constraint
 value-of-land-bid-on-per-acre
 value-of-land-bid-on
 bid
 current-bid
 abs-max-bid
 error2
 initial-parameters
 list-prices
 std-dev-land
 upper-bound
 lower-bound
]

patches-own
 [
 annual-multiplier
 patch-id
 owner
 farmstead?
 for-sale?
 quality
 k-acres
 distance-to-farmstead
 rain
 prodn-volume
 on-auction-block?
 reservation-price
 times-sold
 expected-price-p
 expected-yield-p
 expected-price-per-acre-adj-p
 expected-gross-rev-p
 expected-variable-prodn-costs-p
 expected-hired-labour-cost-p
 expected-transport-cost-p
 expected-capital-replacement-charge-p
 expected-netrev-p
 initial-capital-investment-p
 expected-salvage-value-p
 annuity-p
]

breed [farmers a-farmer]
 breed [retirees retired]

```

.....
.....: INITIALIZATION-PHASE-CONTROL :.....
.....

```

to initialization-phase-control

```

    if user-yes-or-no? "Have Output Files Been Initialized?"
      [ setup ]

```

end

to setup

```

ca
clear-output
create-plots
initialize-farm-agents
import-crop-arrays
delete-files
set simulation 1
prepare-output-files
user-message "initialization complete"

```

end

```

.....
.....: RESET MODEL :.....
.....

```

to reset

```

clear-all-plots
clear-drawing
clear-output
cp
ct
ask turtles [die]
set plots-for-sale 0
set total-plots-sold 0
set total-plots-unsold 0
set plots-unsold-this-tick 0
set reservation-not-met 0
set plots-sold-this-tick 0
set land-price 0
set price-crop 0
set yield-crop 0
set year 0
set tot-vc-prodn 0
set avg-vc-prodn 0
set tot-prodn-crop 0
set avg-prodn-crop 0
set tot-crop-revenue 0
set avg-crop-revenue 0
set avg-cost-prodn 0
set tot-cost-prodn 0
set current-plot-bid-on 0
set current-list-of-bids 0
set current-winning-bid 0
set current-winner 0
set price-paid 0
set highest-bid 0
set second-highest-bid 0

```

```

set adj-winning-bid 0
set list-of-winning-bids-adj 0
set all-prices 0
set auction-winner 0
set auction-seller 0
set auction-plot-acres 0
set auction-plot-quality 0
set auction-plot-location 0
set past-crop-prices 0
set past-crop-yields 0
set xloc 0
set yloc 0
set bidders 0
set land-for-sale? 0
set dead 0
set retired-exit 0
set voluntary-exit 0
set forced-exit 0

end

.....
..... CREATE PLOTS .....
.....

to create-plots
  assign-patch-id
  clear-land-tenure
  set-quality-and-cultivated-acres
end

to assign-patch-id

let counter []
set counter 1
  ask patches [without-interruption [set patch-id counter set counter counter + 1]]
  ask patches [ set pcolor black]
end

to clear-land-tenure
set current-plot-bid-on []
ask patches [set owner "NA"
  set for-sale? true
  set farmstead? false
  set on-auction-block? false
]
end

to set-quality-and-cultivated-acres
ask patches [set quality random-normal 1 0.05]
  diffuse quality 0.75
ask patches [set quality precision quality 2]
ask patches [set pcolor green]
ask patches [set k-acres random-normal 150 15]
  diffuse k-acres 0.5
ask patches [set k-acres precision k-acres 0]
ask patches with [ k-acres > 160 ][set k-acres 160]
ask patches [set times-sold 0]
end

.....
..... CREATE FARM AGENTS .....
.....

```


to initialize-farm-agents

```
create-farm-agents
assign-farm-agent-attributes
create-retirees
```

end

to create-farm-agents

```
create-farmers 422
ask farmers [set color red]
ask farmers [set type-of-exit 0]
ask farmers [set skill random-normal 1 0.05]
ask farmers with [ skill > 1.2][set skill 1.2]
ask farmers [set skill precision skill 2]
ask farmers [set land-value 0]
ask farmers [set asset-value 0]
ask farmers [set debt 0]
ask farmers [set principal 0]
ask farmers [set years-paid-debt 0]
ask farmers [set list-NCFBI ["x" "x" "x" "x" "x"]]
ask farmers [setxy random-xcor random-ycor]
ask farmers [if any? other-turtles-here [ find-new-spot ]]
ask farmers [set xcor pxcor-of patch-at 0 0]
ask farmers [set ycor pycor-of patch-at 0 0]
ask farmers [set owner-of (patch-at 0 0) who]
ask farmers [set buyer? "NA"]
ask farmers [set credit-constrained? "NA"]
ask farmers [set won-last 0]
ask farmers [set winning-bids []]
ask farmers [set capital-purchases []]
ask farmers [set active-bidder? false set plots-purchased 0 set plots-sold 0]
ask patches with [owner != "NA"][set for-sale? false]
ask patches with [owner != "NA"][set farmstead? true]
```

end

to assign-farm-agent-attributes

```
ask farmers
[
  set generation 1
  if Type-of-Auction = "TPSB"
  [
    set local-price-info [ 453.07      470.33  429.67  489.05  483.30  412.91 ]
    set global-price-info [ 386.19      489.70  430.60  469.52  411.88  409.35 ]
  ]
  if Type-of-Auction = "FPSB"
  [
    set local-price-info [ 418.44      438.81  502.74  510.69  435.78  448.48 ]
    set global-price-info [ 439.46      450.97  479.83  493.07  455.44  433.01 ]
  ]
  if Type-of-Auction = "SPSB"
  [
    set local-price-info [ 339.37      345.83  406.06  387.53  453.77  468.30 ]
    set global-price-info [ 468.66      416.59  377.23  347.46  439.05  439.31 ]
  ]
  if Type-of-Auction = "English"
  [
```

```

    set local-price-info [ 397.11      489.25  559.01  418.57  460.15  534.89 ]
    set global-price-info [ 389.97      458.63  410.42  441.13  472.89  503.52 ]
  ]
]

file-open "Initial-Population3.txt"
ask farmers [set initial-parameters file-read]
file-close
file-open "residual-to-land-labor.txt"
ask farmers [set residual-to-land-labor-exp file-read]
file-close
file-open "expected-crop-volume.txt"
ask farmers [set expected-production-volume file-read]
file-close
ask farmers
[
  set age item 0 initial-parameters
  set plots-owned item 1 initial-parameters
  set debt precision(item 2 initial-parameters)2
  set debt precision(debt * 1.15)2
  if age < 20 [set age 20]
]

ask farmers [own]

ask farmers [if age <= 30 [set attitude 3]]           ;; least risk averse
ask farmers [if (age > 30 and age <= 40) [set attitude 2]]           ;;
ask farmers [if (age > 40) [set attitude 1]]           ;; most risk averse

ask farmers [set urgency 1]

ask farmers [set years-paid-debt 1]
;; This assumes that all loans were refinanced in t = 0
ask farmers [set principal debt]
ask farmers [set debt-payment-amount precision(principal * (Int-Rate / (1 - (1 / (1 + Int-Rate)^ repayment))))0]
ask farmers [set principal-paid precision(debt-payment-amount - (principal * Int-Rate))0]
  set debt debt - principal-paid]

ask farmers [set acres-total-crop sum values-from patches with [owner = who-of myself][k-acres]]
ask farmers [set capital-value (capital-per-acre * acres-total-crop)]
ask farmers [set cash precision(cash-per-acre * acres-total-crop)0]

end

to find-new-spot
  fd random 20
  if not can-move? 1
  [ rt random 180 ]
  fd random 15
  if any? other-turtles-here [find-new-spot]
end

to own
  if ((count patches with [owner = who-of myself]) < plots-owned)[find-land]
end

to find-land
  without-interruption [ask min-one-of patches with [for-sale? = true][abs(pxcor - xcor-of myself) + abs(pycor - ycor-of myself)]]
  [set owner who-of myself
   set distance-to-farmstead distancexy xcor-of turtle owner ycor-of turtle owner
   set for-sale? false]

```

```

]]
if ((count patches with [owner = who-of myself])< plots-owned)[find-land]
end

```

```

to create-retirees
ask farmers [if age >= 65 [set breed retirees]]
ask retirees
[
  set color black
  set exit true
  set type-of-exit 1
  set years-retired 1
  set attitude 3
  set urgency 0.85
  set won-last 0
  ask patches with [owner = who-of myself]
  [ set for-sale? true
    set pcolor blue
    set farmstead? false
  ]
]
end

```

```

.....
.....::: ASSIGN PARAMETERS :::.....
.....
.....

```

```

to import-crop-arrays

```

```

  file-open "yield crop.txt"
  set yield-crop file-read
  file-close
  file-open "past crop yield.txt"
  set past-crop-yields file-read
  file-close
  import-price-arrays
end

```

```

to import-price-arrays
  file-open "price crop.txt"
  set price-crop file-read
  file-close
  file-open "past crop price.txt"
  set past-crop-prices file-read
  file-close

```

```

if Type-of-Auction = "TPSB"
[
  set list-of-winning-bids-adj [
    445.43 443.58 440.80 411.37 474.14 379.31 414.69 477.17
    465.46
    361.86 398.46 413.82 396.28 501.12 502.99 426.78 443.93 362.56
    431.14 376.16 "x" "x" "x" "x" "x" "x" "x" "x" "x" "x" "x" "x"
    "x" "x" "x" "x" "x" "x" ]
]
if Type-of-Auction = "FPSB"
[
  set list-of-winning-bids-adj [
    420.60 509.19 464.36 491.95 457.52 474.45 457.16 424.06
    422.57

```

```

                                435.03 463.30  440.00  490.34  454.14  481.35  482.71  438.35  430.11
                                457.07 486.77  "x"      "x"      "x"      "x"      "x"      "x"      "x"
                                "x"      "x"      "x"      "x"      "x"      "x"      "x"      "x"
                                ]
]
if Type-of-Auction = "SPSB"
[
  set list-of-winning-bids-adj [ 385.31 459.87 345.24 356.71 398.99 384.87 454.83 370.96
                                410.55
                                340.92 355.20 360.14 351.59 323.47 467.77 440.71 405.29 419.86
                                433.11 464.87 "x"      "x"      "x"      "x"      "x"      "x"      "x"
                                "x"      "x"      "x"      "x"      "x"      "x"      "x"      "x"
                                ]

]
if Type-of-Auction = "English"
[
  set list-of-winning-bids-adj [ 494.59 527.13 554.63 460.17 558.53 503.82 511.33 507.25
                                425.09
                                405.13 489.72 469.35 492.39 477.63 519.56 488.65 406.47 480.78
                                546.90 486.34 "x"      "x"      "x"      "x"      "x"      "x"      "x"
                                "x"      "x"      "x"      "x"      "x"      "x"      "x"      "x"
                                ]

]

set all-prices list-of-winning-bids-adj
;;; this will be used when learning is off.

ask farmers [set land-value precision((sum values-from patches with [owner = who-of myself ][k-acres * quality]) *
mean list-of-winning-bids-adj)0]
ask farmers [set asset-value precision(land-value + capital-value + cash)0]
ask farmers [set equity-value precision (asset-value - debt)0]

end

.....
..... SIMULATION PHASE CONTROL .....
.....

to simulation-phase

set year year + 1

update-retirees-parameters
update-farmers-parameters
crop-production-module
farm-accounting-module
form-expectations
continue-farming-module?
farm-expansion-contraction
reservation-price-calculation-module
land-purchase-auction-module
export-data
ifelse year < simulation-length
[simulation-phase]
[ifelse simulation < number-of-simulations

```

```

[ set simulation simulation + 1
  reset
  create-plots
  initialize-farm-agents
  import-crop-arrays
  simulation-phase
]
[user-message "complete"]
]
end

to update-retirees-parameters

ask retirees
[
  set years-retired (years-retired + 1)
  set color black
  set exit true
  ask patches with [owner = who-of myself]
  [
    set for-sale? true
    set pcolor blue
    set farmstead? false
  ]
  if years-retired <= 2 [set attitude 3 set urgency 0.85]
  if (years-retired > 2 and years-retired <= 5) [set attitude 2 set urgency 0.75]
  if (years-retired > 5) [set attitude 1 set urgency 0.65]
  ;; maybe this should be a function of farmsize as well? Small farms more urgent.
  ;; Dick says yes, Peter and I say no.
]
end

to update-farmers-parameters
  error-calculation
  ask farmers [if age <= 30 [set attitude 3]]
  ask farmers [if (age > 30 and age <= 40) [set attitude 2]]
  ask farmers [if (age > 40) [set attitude 1]]

  ask farmers [if attitude = 3[set risk-aversion 0.95]]
  ask farmers [if attitude = 2[set risk-aversion 0.90]]
  used in bidding
  ask farmers [if attitude = 1[set risk-aversion 0.85]]
end

.....
..... CROP PRODUCTION MODULE .....
.....

to crop-production-module

simulate-crop-revenue
simulate-variable-prodn-costs
simulate-hired-labour-cost
simulate-transport-cost
simulate-capital-replacement-charge
simulate-living-deductions
set-net-cash-flow-before-investment

end

to simulate-crop-revenue

```

```

set tot-vc-prodn 0
the simulation
set avg-vc-prodn 0
set tot-prodn-crop 0
set avg-prodn-crop 0
set tot-crop-revenue 0
set avg-crop-revenue 0

ask patches [set rain random-normal 1 0.05]
diffuse rain 0.75
ask patches [set rain precision rain 2]

ask patches [set annual-multiplier rain * quality]
;;; calculates yield multiplier (annual and fixed growing condition)
ask farmers [set acres-total-crop sum values-from patches with [owner = who-of myself][k-acres]]
;;; calculates total crop acreage of farm
ask farmers [set average-multiplier
precision ((sum values-from patches with [owner = who-of myself][annual-multiplier * k-acres]) / acres-
total-crop) 2]
ask farmers [set average-soil-quality
precision ((sum values-from patches with [owner = who-of myself][quality * k-acres]) / acres-total-crop)2]

ask farmers [set prodn-crop precision (acres-total-crop * average-multiplier * skill * (item (year) yield-crop))2]
;;; calculates volume of production in tonnes for all k-acres owned of crop

set tot-prodn-crop sum values-from turtles [prodn-crop]
;;; calculates the total production by all agents
set avg-prodn-crop (tot-prodn-crop / 422)
;;; calculates the average production by all agents

ask farmers [set crop-revenue precision (prodn-crop * (item (year) price-crop))2]
;;; calculates crop revenue

set past-crop-prices fput (item (year) price-crop) past-crop-prices
;;; adds current crop price to a vector of past prices
set past-crop-prices but-last past-crop-prices
set past-crop-yields fput (item (year) yield-crop) past-crop-yields
;;; adds current crop yield to a vector of past yields
set past-crop-yields but-last past-crop-yields
set tot-crop-revenue sum values-from turtles [crop-revenue]
;;; calculates total crop revenue for all agents
set avg-crop-revenue (tot-crop-revenue / 422)
;;; calculates average crop revenue for all agents
ask farmers [ask patches with [owner = who-of myself][set prodn-volume (annual-multiplier / average-multiplier-of
myself) *
;;; calculates volume of production on each plot of land (TOTAL: ALL K ACRES)
(prodn-crop-of myself / acres-total-crop-of myself) *
k-acres]]
end
to simulate-variable-prodn-costs
ask farmers [set variable-prodn-costs precision (acres-total-crop * per-acre-vc)0]
set tot-vc-prodn sum values-from turtles [variable-prodn-costs]
set avg-vc-prodn (tot-vc-prodn / 422)
end
to simulate-hired-labour-cost
ask farmers [set hired-labour precision (((0.8 / (1 + 14500 * exp (-0.009 * acres-total-crop))) + 0.03) * acres-total-
crop) * 6.75)0]
end
to simulate-transport-cost

```

```

    ask farmers [set travel-cost (sum values-from patches with [owner = who-of myself][distance-to-farmstead]) *
travel-adjustment]
    ask farmers [set trucking-cost precision (sum values-from patches with [owner = who-of myself]
    [prodn-volume * distance-to-farmstead] * trucking-rate)0]
end
to simulate-capital-replacement-charge
    ask farmers [set capital-replacement-charge capital-value * depreciation-rate]
end

to simulate-living-deductions
    ask farmers [set family-withdrawal precision(min-family-withdrawal + 0.068 * crop-revenue + 125 * (plots-
owned))0]

end

to set-net-cash-flow-before-investment
    set tot-cost-prodn 0
    set avg-cost-prodn 0
    ask farmers [ set tc-prodn 0]
    ask farmers [ set tc-prodn (variable-prodn-costs + hired-labour + travel-cost + trucking-cost + capital-replacement-
charge)]
    ask farmers [ if debt = 0
        [set NCFBI precision(crop-revenue - tc-prodn - debt-payment-amount - family-withdrawal)0]]
    ask farmers [ if debt > 0 and debt >= debt-payment-amount
        [set NCFBI precision(crop-revenue - tc-prodn - debt-payment-amount - family-withdrawal)0]]
    ask farmers [ if debt > 0 and debt < debt-payment-amount
        [set NCFBI precision(crop-revenue - tc-prodn - debt - family-withdrawal)0]]
    ask farmers [set cash (cash + NCFBI)]
    ask farmers [set list-NCFBI fput NCFBI list-NCFBI]
    ask farmers [set list-NCFBI butlast list-NCFBI]

    ask farmers [ifelse (cash < 0)
        [set years-neg-cash years-neg-cash + 1][set years-neg-cash 0]]
    ask farmers [if cash < 0 [ set debt (debt + (cash * -1)) set cash 0]]

    ask farmers [ifelse (NCFBI < 0)
        [set years-neg-ncfbi years-neg-ncfbi + 1][set years-neg-ncfbi 0]]

    ask farmers [set principal-paid precision(debt-payment-amount - (principal * Int-Rate))0
    set debt debt - principal-paid]

    ask farmers [ if debt <= 0
        [set debt 0 set principal 0 set debt-payment-amount 0 set years-paid-debt 0 set principal-paid 0]]

    set tot-cost-prodn sum values-from turtles [tc-prodn]
    set avg-cost-prodn mean values-from turtles [tc-prodn]
end

.....
.....; FARM ACCOUNTING MODULE .....
.....

to farm-accounting-module

    ask farmers [determine-land-market-value]
    ask farmers [determine-asset-value]
    ask farmers [determine-equity-value]

end

to determine-land-market-value

```

```

    set land-value precision((sum values-from patches with [owner = who-of myself ][k-acres * quality]) * mean list-
of-winning-bids-adj)0
end

```

```

to determine-asset-value
    set asset-value precision(land-value + capital-value + cash)0
end

```

```

to determine-equity-value
    set equity-value precision (asset-value - debt)0
end

```

```

.....
.....; EXPECTATIONS MODULE? .....
.....

```

```

to form-expectations
ask farmers [set residual-to-land-labor precision
    (((crop-revenue / average-soil-quality)
    - variable-prodn-costs
    - capital-replacement-charge
    - (0.068 * crop-revenue)
    - (125 * (plots-owned)))
    / acres-total-crop)2]

```

```

ask farmers [ifelse residual-to-land-labor >= residual-to-land-labor-exp
    [set residual-to-land-labor-exp (residual-to-land-labor-exp * (1 - expectation-weight)
    + (expectation-weight * residual-to-land-labor))]
    [set residual-to-land-labor-exp (residual-to-land-labor-exp * (1 - (1 * expectation-weight))
    + ((1 * expectation-weight) * residual-to-land-labor))]]

```

```

ask farmers [set expected-production-volume precision
    ((expected-production-volume * (1 - expectation-weight)) +
    (prodn-crop / average-soil-quality / acres-total-crop)* expectation-weight)0]

```

```

.....; LAND PRICE EXPECTATION INFORMATION .....

```

```

if Information-Diffusion = "on"

```

```

[ask patches

```

```

    [
        set expected-price-per-acre-adj-p (.7 * ((0.38 * item 0 local-price-info-of turtle owner) +
        (0.28 * item 1 local-price-info-of turtle owner) +
        (0.16 * item 2 local-price-info-of turtle owner) +
        (0.08 * item 3 local-price-info-of turtle owner) +
        (0.07 * item 4 local-price-info-of turtle owner) +
        (0.03 * item 5 local-price-info-of turtle owner)) + .3 * ((0.38 * item 0 global-price-
info-of turtle owner) +
        (0.28 * item 1 global-price-info-of turtle owner) +
        (0.16 * item 2 global-price-info-of turtle owner) +
        (0.08 * item 3 global-price-info-of turtle owner) +
        (0.07 * item 4 global-price-info-of turtle owner) +
        (0.03 * item 5 global-price-info-of turtle owner)))
    ]

```

```

ask turtles

```

```

    [
        set expected-price-per-acre-adj (.7 * ((0.38 * item 0 local-price-info) +
        (0.28 * item 1 local-price-info) +
        (0.16 * item 2 local-price-info) +
        (0.08 * item 3 local-price-info) +
        (0.07 * item 4 local-price-info) +

```



```

(0.03 * item 5 local-price-info)) + .3 * ((0.38 * item 0 global-price-info) +
(0.28 * item 1 global-price-info) +
(0.16 * item 2 global-price-info) +
(0.08 * item 3 global-price-info) +
(0.07 * item 4 global-price-info) +
(0.03 * item 5 global-price-info)))
]
]

if Information-Diffusion = "off"
[ask patches
[
let standard-dev standard-deviation all-prices
let average mean all-prices
set expected-price-per-acre-adj-p precision(random-normal average standard-dev)2
]
ask turtles
[
let standard-dev standard-deviation all-prices
let average mean all-prices
set expected-price-per-acre-adj precision(random-normal average standard-dev)2
]
]
];, OUTPUT PRICE AND YIELD EXPECTATION INFORMATION ;,
ask patches
[
set expected-price-p precision(((0.40 * (item 0 past-crop-prices))+(0.20 * (item 1 past-crop-prices))+
(0.15 * (item 2 past-crop-prices)) + (0.15 * (item 3 past-crop-prices))+
(0.10 * (item 4 past-crop-prices))) * (1 + error2-of turtle owner))2
set expected-yield-p precision(((0.40 * (item 0 past-crop-yields))+(0.20 * (item 1 past-crop-yields))+
(0.15 * (item 2 past-crop-yields)) + (0.15 * (item 3 past-crop-yields))+
(0.10 * (item 4 past-crop-yields))) * (1 + error2-of turtle owner))2
]
ask turtles
[
set expected-price precision(((0.40 * (item 0 past-crop-prices))+(0.20 * (item 1 past-crop-prices))+
(0.15 * (item 2 past-crop-prices)) + (0.15 * (item 3 past-crop-prices))+
(0.10 * (item 4 past-crop-prices))) * (1 + error2))2
set expected-yield precision(((0.40 * (item 0 past-crop-yields))+(0.20 * (item 1 past-crop-yields))+
(0.15 * (item 2 past-crop-yields)) + (0.15 * (item 3 past-crop-yields))+
(0.10 * (item 4 past-crop-yields))) * (1 + error2))2
]
]
end

;,,
;,, CONTINUE FARMING MODULE? ;,,
;,,

to continue-farming-module?

ask farmers [set exit false]
ask farmers [set buyer? "na"]

ask farmers with [ years-neg-cash = 0][set urgency 1]
ask farmers with [ years-neg-cash = 1][set urgency 0.80]
ask farmers with [ years-neg-cash = 2][set urgency 0.60]
ask farmers with [ years-neg-cash >= 3][set urgency 0.50]
;,, years-neg-cash not yet used --> urgency not used for farmers yet either.

```

```

ask farmers with [(age >= 55) and (age < 60)][if (random 100 < retirement-tendency-55-59 * 100) [set exit true
set type-of-exit 1]]
ask farmers with [(age >= 60) and (age < 65)][if (random 100 < retirement-tendency-60-64 * 100) [set exit true
set type-of-exit 1]]
ask farmers with [(age >= 65) and (age < 70)][if (random 100 < retirement-tendency-65-69 * 100) [set exit true
set type-of-exit 1]]
ask farmers with [age >= 70] [if (random 100 < retirement-tendency-70-over * 100)[set exit true set
type-of-exit 1]]
ask farmers with [age >= 80] [set exit true set type-of-exit 1]

ask farmers with [exit = true] [if (random 100 < percent-pass-down and equity-value / asset-value > 0.6)
[set exit false set type-of-exit 0 next-generation]]
;; random X% of farmers with equity/asst > 60% pass down land

ask farmers [if years-neg-ncfbi >= (random 5 + 5)[set exit true set type-of-exit 2]] ;; Voluntary
exit b/c of equity erosion
ask farmers [if (debt) > (0.9 * asset-value)[set exit true set type-of-exit 3]] ;; Forced exit b/c
of Insolvency

ask farmers with [exit = true]
[
let to-print (list "1" simulation year who age breed type-of-exit generation skill attitude plots-owned average-soil-
quality
risk-aversion debt asset-value years-neg-ncfbi "1")
file-open "retiree-info.txt"
file-print to-print
file-close

set breed retirees
set color black
set years-retired 1
set attitude 3
set urgency 0.85
ask patches with [owner = who-of myself]
[
set for-sale? true
set pcolor blue
set farmstead? false
]
]

end

to next-generation

without-interruption
[
let to-print (list "1" simulation year who age generation skill attitude risk-aversion debt asset-value "1")
file-open "pass-on-stats.txt"
file-print to-print
file-close

set generation generation + 1
set age age - 30
if age < 20 [set age 20]
set age int age
set attitude 3
set risk-aversion 0.95

]
end

```

```

.....
.....;;FARM EXPANSION/CONTRACTION MODULE .....
.....

to farm-expansion-contraction
  set plots-unsold-this-tick 0
  set plots-sold-this-tick 0
  set credit-constrained 0
  ask farmers [
    without-interruption
    [
      ask farmers with [buyer? != "seller"] [screen-farmers]
      ask farmers with [buyer? = "seller"] [farm-contraction]

    ]
  ]
end

to screen-farmers
  if ((cash > (10 * acres-total-crop + 150 * mean list-of-winning-bids-adj * downpayment))
  Liquidity check
  and ((debt / asset-value) < D-A-ratio)
  and ((debt-payment-amount + min-family-withdrawal) < (residual-to-land-labor-exp * acres-total-
  crop))
  and (age <= 55) )
  [set buyer? "buyer" farm-expansion]
end

to farm-expansion
  set color pink
end

to farm-contraction
  without-interruption
  [
    set color yellow
    if plots-owned = 1 [ask patches with [owner = who-of myself] [set farmstead? false]]

    set plot-for-sale patch-id-of min-one-of patches with [owner = who-of myself and farmstead? = false] [distance-
    to-farmstead]
    ask patches with [patch-id = plot-for-sale-of myself] [set for-sale? true set pcolor blue]
  ]
end

.....
.....;;RESERVATION PRICE CALCULATION MODULE .....
.....

to reservation-price-calculation-module
  ifelse reservation-price?
  [
    without-interruption
    [ask patches with [for-sale? = true]
    [
      set reservation-price 0
      set reservation-price precision (expected-price-per-acre-adj-p * k-acres-of self * quality-of self *
      skill-of turtle owner * urgency-of turtle owner * (1 + error2-of turtle owner))2
      without-interruption
      [
        let to-print (list "1" simulation year quality k-acres reservation-price "1")
        file-open "reservation-prices.txt"
        file-print to-print
      ]
    ]
  ]
]

```

```

        file-close
    ]
]
]]
[ask patches with [for-sale? = true]
  [set reservation-price 0]
]
end

```

```

.....
.....: LAND PURCHASE AUCTION MODULE .....
.....

```

```

to land-purchase-auction-module
  ask farmers [set active-bidder? false]
  set current-winning-bid 0
  set current-winner 0
  set current-list-of-bids []
  set price-paid 0
  set auction-winner "na"
  set auction-seller "na"

  set plots-for-sale (count patches with [for-sale? = true])
  ifelse count patches with [for-sale? = true] > 0 [set land-for-sale? true][set land-for-sale? false]
  if land-for-sale? = true
  [
    auction-block
    decide-to-bid
    ifelse bidders > 0
      [max-bid-calculation]
      [ask patches with [on-auction-block? = true]
        [
          set for-sale? false
          set current-plot-bid-on ""
          set on-auction-block? false
          set pcolor green
          set auction-seller "na"
          set auction-plot-acres ""
          set auction-plot-quality ""
          set xloc ""
          set yloc ""
          ask farmers with [who = owner-of myself][set buyer? "na" set color red set plot-for-sale false]
          set total-plots-unsold total-plots-unsold + 1
          set plots-unsold-this-tick plots-unsold-this-tick + 1
        ]
      ]
    ]
    ifelse bidders > 0
      [compare-bids submit-highest-bid]
      [ask patches with [on-auction-block? = true]
        [
          set for-sale? false
          set current-plot-bid-on ""
          set on-auction-block? false
          set pcolor green
          set auction-seller "na"
          set auction-plot-acres ""
          set auction-plot-quality ""
          set xloc ""
          set yloc ""
          ask farmers with [who = owner-of myself][set buyer? "na" set color red set plot-for-sale false]
          set total-plots-unsold total-plots-unsold + 1
          set plots-unsold-this-tick plots-unsold-this-tick + 1
        ]
      ]
    ]
  ]
end

```

```

    ]]
    land-purchase-auction-module
  ]
end

```

```

.....
.....FIND LAND AND BUYERS MODULE.....
.....

```

```

to auction-block
  ask one-of patches with [for-sale? = true] [set on-auction-block? true
    set current-plot-bid-on patch-id-of self
    set auction-seller owner-of self
    set auction-plot-acres k-acres-of self
    set auction-plot-quality quality-of self
    set xloc pxcor-of self
    set yloc pycor-of self
    watch-me]
end

```

```

to decide-to-bid
  ask farmers with [buyer? = "buyer"]
  [
    set winning? false
    set winner? false
    set credit-constrained? false

    set distance-to-plot-bid-on distancexy xloc yloc
    ifelse distance-to-plot-bid-on <= max-distance-travel
      [set active-bidder? true]
      [set active-bidder? false]
  ]
  set bidders count farmers with [active-bidder? = true]
end

```

```

.....
.....COMPARE AND SUBMIT BIDS MODULE.....
.....

```

```

to compare-bids
  if bidders = 1
  [
    without-interruption[
      ask farmers with [active-bidder? = true][
        set times-bid times-bid + 1
        set won-last 2

        set auction-winner who-of self
        set winning? true
        set winner? true
        set current-bid ((bid + reservation-price-of patch xloc yloc) / 2)
        set highest-bid current-bid
        set price-paid current-bid
      ]]]
  ]
end

```

```

if bidders > 1
[
  without-interruption[
    ask farmers with [active-bidder? = true][
      set times-bid times-bid + 1
      set won-last 2
    ]
  ]
end

```

```

if Type-of-Auction = "TPSB"
[
  if bidders < 3
    [set bidders 3 set current-list-of-bids lput reservation-price-of patch xloc yloc current-list-of-bids
      set current-list-of-bids lput reservation-price-of patch xloc yloc current-list-of-bids]
  let N bidders
  set bid precision(value-of-land-bid-on * ((N - 1)/(N - 2)))2
  ifelse bid >= max-bid
    [set current-bid max-bid]
    [set current-bid bid]
  set current-list-of-bids lput current-bid current-list-of-bids
  if current-bid > current-winning-bid
    [ set current-winning-bid current-bid set current-winner who-of self ]

  ifelse current-winner = who-of self
    [set winning? true set winner? true]
    [set winning? false set winner? false]

  set highest-bid current-winning-bid
  set auction-winner current-winner
]
if Type-of-Auction = "FPSB"
[
  let N bidders
  set bid precision((value-of-land-bid-on * (N - 1)/ N)2
  ifelse bid >= max-bid
    [set current-bid max-bid]
    [set current-bid bid]
  set current-list-of-bids lput current-bid current-list-of-bids
  if current-bid > current-winning-bid
    [ set current-winning-bid current-bid set current-winner who-of self ]

  ifelse current-winner = who-of self
    [set winning? true set winner? true]
    [set winning? false set winner? false]

  set highest-bid current-winning-bid
  set price-paid current-winning-bid
  set auction-winner current-winner
]
if Type-of-Auction = "English"
[
  if value-of-land-bid-on-per-acre < max-bid-per-acre    ;;
    [set bid value-of-land-bid-on set abs-max-bid max-bid] ;;
    ;;
  if value-of-land-bid-on-per-acre > max-bid-per-acre    ;;
    [set bid max-bid set abs-max-bid max-bid]           ;;
    ;;
  set current-bid bid

  set current-list-of-bids lput current-bid current-list-of-bids
  if current-bid > current-winning-bid
    [ set second-highest-bid current-winning-bid set current-winning-bid current-bid set current-winner who-of self
]

ifelse current-winner = who-of self
  [set winning? true]
  [set winning? false]
set highest-bid (second-highest-bid * (1 + (minimum-bid-increment / 100)))

;; All farmers have calculated and submitted highest bid. They now wait here until they are all done and then
;; move on to the next part of the English auction below.

```

```

]

if Type-of-Auction = "SPSB"
[
  if value-of-land-bid-on-per-acre < max-bid-per-acre    ;
    [set bid value-of-land-bid-on]                      ;
                                ; Bid set bid min of MaxWTP and Est. Value
  if value-of-land-bid-on-per-acre > max-bid-per-acre    ; Optimal Strategy is to "tell the truth"
    [set bid max-bid]                                    ;

  set current-bid bid
  set current-list-of-bids lput current-bid current-list-of-bids
  if current-bid > current-winning-bid
    [ set second-highest-bid current-winning-bid set current-winning-bid current-bid set current-winner who-of self
]

  ifelse current-winner = who-of self
    [set winning? true set winner? true]
    [set winning? false set winner? false]

  set highest-bid current-winning-bid
  set price-paid second-highest-bid
  set auction-winner current-winner
]
]]]
;;; Part two of English Auction. Begins only AFTER all first round bids have been submitted and a leader is chosen.

if Type-of-Auction = "English"
[
  set current-winning-bid highest-bid
  ask farmers with [active-bidder? = true and abs-max-bid >= highest-bid]
  [
    ifelse (attitude = 1 and random 100 < 20)
      [set current-bid abs-max-bid]
      [set current-bid bid]
    ifelse (attitude = 2 and random 100 < 50)
      [set current-bid abs-max-bid]
      [set current-bid bid]
    ifelse (attitude = 3 and random 100 < 80)
      [set current-bid abs-max-bid]
      [set current-bid bid]
  ]
  ask farmers with [active-bidder? = true and current-bid >= highest-bid]
  [
    without-interruption [
      set current-list-of-bids lput "X" current-list-of-bids
      set current-list-of-bids lput current-bid current-list-of-bids
      if current-bid > current-winning-bid
        [set second-highest-bid current-winning-bid set current-winning-bid current-bid set current-winner who-of
self]
      ifelse current-winner = who-of self
        [set winning? true set winner? true]
        [set winning? false set winner? false]
      set highest-bid (second-highest-bid * (1 + (minimum-bid-increment / 100)))
      set price-paid highest-bid
      set auction-winner current-winner
    ]
  ]
]

end
to submit-highest-bid

```

```

if Type-of-Auction = "TPSB"
  [let list-bids sort current-list-of-bids
   set list-bids but-last list-bids
   set list-bids but-last list-bids
   set price-paid last list-bids]
ifelse price-paid >= reservation-price-of patch xloc yloc
[
  let to-print (list "1" simulation year current-plot-bid-on auction-seller auction-plot-acres
                    auction-plot-quality auction-winner highest-bid price-paid second-highest-bid "1")
  file-open "bidding-details.txt"
  file-print to-print
  file-close
  let to-print6 (list "1" simulation year current-plot-bid-on bidders auction-winner auction-seller
                    reservation-price-of patch xloc yloc distance-to-plot-bid-on-of turtle auction-winner
                    max-bid-of turtle auction-winner max-bid-credit-constraint-of turtle auction-winner
                    value-of-land-bid-on-of turtle auction-winner bid-of turtle auction-winner
                    current-bid-of turtle auction-winner abs-max-bid-of turtle auction-winner price-paid
                    credit-constrained?-of turtle auction-winner (max-bid-of turtle auction-winner - price-paid)
                    (price-paid - reservation-price-of patch xloc yloc) times-bid-of turtle auction-winner
                    won-last-of turtle auction-winner "1")
  file-open "winner-details.txt"
  file-print to-print6
  file-close

  transfer-ownership
]
[
  let to-print (list "1" simulation year price-paid reservation-price-of patch xloc yloc "1")
  file-open "unmet-reservations.txt"
  file-print to-print
  file-close
  ask patches with [on-auction-block? = true]
  [
    set for-sale? false
    set current-plot-bid-on ""
    set on-auction-block? false
    set pcolor green
    set auction-seller "na"
    set auction-plot-acres ""
    set auction-plot-quality ""
    set xloc ""
    set yloc ""
    ask farmers with [who = owner-of myself][set buyer? "na" set color red set plot-for-sale false]
    set total-plots-unsold total-plots-unsold + 1
    set plots-unsold-this-tick plots-unsold-this-tick + 1
    set reservation-not-met reservation-not-met + 1
  ]
]
end
.....
.....: BID FORMATION AND LEARNING MODULE :.....
.....
to max-bid-calculation

without-interruption[
  ask farmers with [active-bidder? = true]
  [
    set upper-bound 0
    set lower-bound 0
    set max-bid 0
    set max-bid-per-acre 0
    set value-of-land-bid-on-per-acre 0

```



```

set value-of-land-bid-on 0
set bid 0
set current-bid 0
set expected-salvage-value 0
set annuity 0
set distance-to-plot-bid-on precision(distanceexy xloc yloc)2
set credit-constrained? false

set expected-gross-rev precision (expected-price * expected-yield * 150 * 1 * risk-aversion * skill)0

set expected-variable-prodn-costs precision (per-acre-vc * 150)0

set expected-hired-labour-cost precision (((0.8 / (1 + 14500 * exp (-0.009 * 150))) + 0.03) * 150) * 6.75)0

set expected-transport-cost precision ((distance-to-plot-bid-on * travel-adjustment) +
(150 * distance-to-plot-bid-on * trucking-rate * expected-yield))0
set expected-capital-replacement-charge precision (capital-per-acre * depreciation-rate * 150)0
set expected-netrev-per-acre precision (( expected-gross-rev
- expected-variable-prodn-costs
- expected-hired-labour-cost
- expected-transport-cost
- expected-capital-replacement-charge) / 150)0          ;; E[Net Rev]/acre
set initial-capital-investment capital-per-acre          ;; capital/acre cost of
purchasing this land
set expected-salvage-value precision((expected-price-per-acre-adj * skill * (1 + error2))
/ ((1 + Int-Rate) ^ (72 - age)))0

set annuity precision ((1 - (1 / (1 + Int-Rate) ^ (72 - age))) * (expected-netrev-per-acre / Int-Rate))0    ;;
annuity/acre

set max-bid-per-acre precision (annuity + expected-salvage-value - initial-capital-investment)2
;;; maximum bid per acre for this particular plot of land
;;; based on ability to generate income from
E[Y,P]

set max-bid precision (max-bid-per-acre * auction-plot-acres * auction-plot-quality)2
;;; maximum bid for this particular plot of land
;;; based on ability to generate income from
E[Y,P]
set max-bid-credit-constraint precision ((mean list-NCFBI * ((1 - (1 / (1 + int-rate) ^ repayment))) / int-rate) / (1
- downpayment))2
;;; maximum bid for this particular plot of
land
;;; based on borrowing constraints

if max-bid-credit-constraint <= max-bid [          ;;; if credit constraints are
binding adjust max-bid
set max-bid max-bid-credit-constraint          ;;; and max-bid-per-acre
set max-bid-per-acre precision
(max-bid / auction-plot-acres / auction-plot-quality)2
set credit-constrained? true
set credit-constrained credit-constrained + 1
]

if (max-bid <= 0 or cash < (max-bid * downpayment)) [set active-bidder? false set max-bid 0 set max-bid-per-
acre 0]
;;; check that bid is > 0 and that there is
enough
;;; cash for a downpayment

set bidders count farmers with [active-bidder? = true]

```

```

]]
ask farmers with [active-bidder? = true][determine-land-value]
end

.....
.....; LAND VALUATION MODULE .....
.....

to determine-land-value
set list-prices sentence local-price-info global-price-info
set std-dev-land standard-deviation list-prices
if attitude = 2 and distance-to-plot-bid-on <= 16
[
set upper-bound precision(expected-price-per-acre-adj + (2 * std-dev-land))2
set lower-bound precision(expected-price-per-acre-adj - (2 * std-dev-land))2
]

if attitude = 2 and distance-to-plot-bid-on > 16 [
set upper-bound precision(expected-price-per-acre-adj + (1 * std-dev-land))2
set lower-bound precision(expected-price-per-acre-adj - (3 * std-dev-land))2
]

if attitude = 1 and distance-to-plot-bid-on <= 16
[
set upper-bound precision(expected-price-per-acre-adj + (1 * std-dev-land))2
set lower-bound precision(expected-price-per-acre-adj - (3 * std-dev-land))2
]

if attitude = 1 and distance-to-plot-bid-on > 16
[
set upper-bound precision(expected-price-per-acre-adj + (0.3 * std-dev-land))2
set lower-bound precision(expected-price-per-acre-adj - (3 * std-dev-land))2
]

if attitude = 3 and distance-to-plot-bid-on <= 16
[
set upper-bound precision(expected-price-per-acre-adj + (3 * std-dev-land))2
set lower-bound precision(expected-price-per-acre-adj - (1 * std-dev-land))2
]

if attitude = 3 and distance-to-plot-bid-on > 16
[
set upper-bound precision(expected-price-per-acre-adj + (2 * std-dev-land))2
set lower-bound precision(expected-price-per-acre-adj - (2 * std-dev-land))2
]
set value-of-land-bid-on-per-acre precision (random-normal expected-price-per-acre-adj std-dev-land)2

if Bid-Adjustment-Strategy = "learning-direction-theory"
[
if won-last = 0 [set value-of-land-bid-on-per-acre value-of-land-bid-on-per-acre]
if won-last = 2 [set value-of-land-bid-on-per-acre precision(value-of-land-bid-on-per-acre * (1 + (bidding-
adjustment / 100)))2]
if won-last = 1 [set value-of-land-bid-on-per-acre precision(value-of-land-bid-on-per-acre * (1 - (bidding-
adjustment / 100)))2]
]

if value-of-land-bid-on-per-acre >= upper-bound
[set value-of-land-bid-on-per-acre upper-bound]
if value-of-land-bid-on-per-acre <= lower-bound
[set value-of-land-bid-on-per-acre lower-bound]

```

```

if (value-of-land-bid-on-per-acre <= 0)
  [set active-bidder? false set max-bid 0 set value-of-land-bid-on-per-acre 0 set upper-bound 0 set lower-
bound 0]
set value-of-land-bid-on precision (value-of-land-bid-on-per-acre * auction-plot-acres * auction-plot-quality)2
set bidders count farmers with [active-bidder? = true]

end

.....
..... LAND TRANSFER AND UPDATES .....
.....

to transfer-ownership
set adj-winning-bid precision ((price-paid / auction-plot-acres) / auction-plot-quality ) 2
let to-print (list "1" simulation year adj-winning-bid "1")
file-open "adjusted-winning-bids.txt"
file-print to-print
file-close
;;; This takes the winning bid and converts it to per acre quality =1 (risk and skill = 1)
set list-of-winning-bids-adj fput adj-winning-bid list-of-winning-bids-adj
set list-of-winning-bids-adj but-last list-of-winning-bids-adj
  ;; list of winning bids decays - has memory
set all-prices fput adj-winning-bid all-prices
  ;; all-prices does not decay

local-global-price-information
ask turtle auction-winner
[
  set cash precision(cash - (downpayment * price-paid))0
  set debt precision(debt + ((1 - downpayment) * price-paid))0
  set principal debt
  refinance-debt
  set winning-bids fput price-paid winning-bids
  set plots-owned plots-owned + 1
  set plots-purchased plots-purchased + 1
  set acres-total-crop acres-total-crop + k-acres-of patch xloc yloc
  set buyer? "NA"
  set active-bidder? false
  set winning? false
  set winner? false
  set color red
  set won-last 1
  capital-purchases-module
  set total-plots-sold total-plots-sold + 1
  set plots-sold-this-tick plots-sold-this-tick + 1
  if ((cash > (10 * acres-total-crop + 150 * mean list-of-winning-bids-adj * downpayment))
  ;;
  Liquidity check
    and ((debt / asset-value) < D-A-ratio)
    and ((debt-payment-amount + min-family-withdrawal) < (residual-to-land-labor-exp * acres-total-
crop))
    and (age <= 55) )
    [set buyer? "buyer" set color pink]
  ]

ask turtle auction-seller
[
  set cash cash + price-paid
  set plots-owned plots-owned - 1
  set plots-sold plots-sold + 1
  set acres-total-crop acres-total-crop - k-acres-of patch xloc yloc
  set plot-for-sale false
  set buyer? "NA"

```

```

    if breed = farmers [set color red]
  ]
  ask patch xloc yloc
  [
    set times-sold times-sold + 1
    set owner auction-winner
    set for-sale? false
    set distance-to-farmstead distancexy xcor-of turtle owner ycor-of turtle owner
    set current-plot-bid-on ""
    set on-auction-block? false
    set pcolor green
    set auction-plot-acres ""
    set auction-plot-quality ""
    set xloc ""
    set yloc ""
    ask turtle auction-seller
    [ determine-land-market-value
      determine-asset-value
      determine-equity-value
      set auction-seller "na"]
  ]

  ask turtles
  [ set credit-constrained? "na"
    if plots-owned <= 0
    [
      let to-print2 (list "1" simulation year who breed age type-of-exit generation plots-sold skill attitude risk-
        aversion asset-value debt "1")
      file-open "exit-stats.txt"
      file-print to-print2
      file-close
      if type-of-exit = 1 [set retired-exit retired-exit + 1]
      if type-of-exit = 2 [set voluntary-exit voluntary-exit + 1]
      if type-of-exit = 3 [set forced-exit forced-exit + 1]
      die
    ]
  ]
]

end

.....
;;;;;;DIFFUSION: LOCAL AND GLOBAL PRICE INFORMATION ;;;;;;;;;
.....

to local-global-price-information

ask retirees[
  without-interruption[
    set local-price-info fput adj-winning-bid local-price-info
    set local-price-info but-last local-price-info
  ]
]

if Information-Diffusion = "on"
[
  without-interruption
  [
    ask turtles with [active-bidder? = false]   ;; Farmers present in auction do not get noisy price b/c they know
    true price
    [
      let true-price adj-winning-bid
      let X distancexy xloc yloc
      let skew one-of [1 -1]

```

```

        let error (skew * (X ^ 1 / 2))
        let observed-price precision(true-price + error)2
        set global-price-info fput observed-price global-price-info
        set global-price-info but-last global-price-info
    ]
]

ask farmers with [active-bidder?]
[
    set local-price-info fput adj-winning-bid local-price-info
    set local-price-info but-last local-price-info
]
]

end

.....
.....: PAYMENTS AND PURCHASES MODULE :.....
.....

to capital-purchases-module

let capital-purchase capital-per-acre * k-acres-of patch xloc yloc
set capital-value precision(capital-value + capital-purchase)0
set cash precision(cash - capital-purchase)0
set capital-purchases fput capital-purchase capital-purchases

determine-land-market-value
determine-asset-value
determine-equity-value

end

.....
.....: REFINANCE DEBT MODULE :.....
.....

to refinance-debt

set debt-payment-amount precision(debt * (Int-Rate / (1 - (1 / (1 + Int-Rate)^ repayment))))0
ifelse debt > 0
[
    ifelse debt > debt-payment-amount
    [set debt-payment-amount debt-payment-amount][set debt-payment-amount debt]
][set debt-payment-amount 0]
end

.....
.....: ERROR CALCULATION :.....
.....

to error-calculation
ask farmers
[
    let skew one-of [1 -1] ;; rethink these.
    if skill > 1.08 [set error2 (random-float 5 * skew) / 100]
    if skill >= 1 and skill <= 1.08 [set error2 (random-float 10 * skew) / 100]
    if skill < 1 and skill >= 0.92 [set error2 (random-float 15 * skew) / 100]
    if skill < 0.92 [set error2 (random-float 20 * skew) / 100 ]
]
end

```

```

.....
..... UPDATE DATA AND PARAMETERS .....
.....
to export-data

ask turtles [set age age + 1]
ask farmers with [cash > 0][set cash precision(cash * 1.02) 0]
ask farmers with [buyer? = "buyer"]
  [ set color red set buyer? "na"]

ask farmers [determine-land-market-value]
ask farmers [determine-asset-value]
ask farmers [determine-equity-value]

let to-print7 (list "1" simulation year mean values-from farmers [residual-to-land-labor-exp] mean values-from
farmers [residual-to-land-labor] "1" )
file-open "financial-information.txt"
file-print to-print7
file-close

without-interruption[
ask farmers[
let to-print (list "1" simulation year who skill acres-total-crop average-soil-quality prodn-crop crop-revenue tc-
prodn debt-payment-amount
family-withdrawal NCFBI principal debt asset-value cash capital-value land-value
(debt / asset-value) times-bid plots-purchased plots-sold"1")
file-open "production-information.txt"
file-print to-print
file-close
]]

set dead (422 - (count turtles))

let to-print3 (list "1" simulation year mean values-from farmers [(debt / asset-value)] mean values-from farmers
[land-value] mean values-from farmers [capital-value]
mean values-from farmers [cash] mean values-from farmers [debt] mean values-from farmers [acres-
total-crop]
mean values-from farmers [skill] mean values-from farmers [ncfbi / acres-total-crop] "1")
file-open "mean-info.txt"
file-print to-print3
file-close

let to-print4 (list "1" simulation year dead retired-exit voluntary-exit forced-exit plots-sold-this-tick plots-unsold-
this-tick
reservation-not-met credit-constrained count farmers with [generation > 1] "1")
file-open "general-info.txt"
file-print to-print4
file-close

end

.....
..... DELETE OUTPUT FILES .....
.....
to delete-files
if "yes" = (user-one-of
"Do You Want to Erase all Output Files?"
["no" "yes"]))
[ delete ]

```

end

to delete

```
file-open "pass-on-stats.txt"
file-write ""
file-close
file-open "bidding-details.txt"
file-write ""
file-close
file-open "exit-stats.txt"
file-write ""
file-close
file-open "unmet-reservations.txt"
file-write ""
file-close
file-open "reservation-prices.txt"
file-write ""
file-close
file-open "adjusted-winning-bids.txt"
file-write ""
file-close
file-open "financial-information.txt"
file-write ""
file-close
file-open "production-information.txt"
file-write ""
file-close
file-open "general-info.txt"
file-write ""
file-close
file-open "mean-info.txt"
file-print ""
file-close
file-open "retiree-info.txt"
file-print ""
file-close
file-open "winner-details.txt"
file-print ""
file-close
```

```
file-delete "pass-on-stats.txt"
file-delete "bidding-details.txt"
file-delete "exit-stats.txt"
file-delete "unmet-reservations.txt"
file-delete "reservation-prices.txt"
file-delete "adjusted-winning-bids.txt"
file-delete "financial-information.txt"
file-delete "production-information.txt"
file-delete "general-info.txt"
file-delete "mean-info.txt"
file-delete "retiree-info.txt"
file-delete "winner-details.txt"
```

end

```
.....
.....: PREPARE OUTPUT FILES :.....
.....
```

```
to prepare-output-files
file-open "pass-on-stats.txt"
```

```

file-write (list "1" "simulation" "year" "who" "age" "generation" "skill" "attitude" "risk-aversion" "debt" "asset-
value" "1")
file-close
file-open "bidding-details.txt"
file-write (list "1" "simulation" "year" "current-plot-bid-on" "auction-seller" "auction-plot-acres"
"auction-plot-quality" "auction-winner" "highest-bid" "price-paid" "second-highest-bid" "1")
file-close
file-open "exit-stats.txt"
file-write (list "1" "simulation" "year" "who" "breed" "age" "type-of-exit" "generation" "plots-sold" "skill"
"attitude" "risk-aversion" "asset-value" "debt" "1")
file-close
file-open "unmet-reservations.txt"
file-write (list "1" "simulation" "year" "price-paid" "reservation-price" "1")
file-close
file-open "reservation-prices.txt"
file-write (list "1" "simulation" "year" "quality" "k-acres" "reservation-price" "1")
file-close
file-open "adjusted-winning-bids.txt"
file-write (list "1" "simulation" "year" "adj-winning-bid" "1")
file-close
file-open "financial-information.txt"
file-write (list "1" "simulation" "year" "Mean-E[PM]" "Mean-[PM]" "1" )
file-close
file-open "production-information.txt"
file-write (list "1" "simulation" "year" "who" "skill" "acres-total-crop" "average-soil-quality" "prodn-crop" "crop-
revenue" "tc-prodn"
"debt-payment-amount" "family-withdrawal" "NCFBI" "principal" "debt" "asset-value" "cash" "capital-
value"
"land-value" "D/A" "times-bid" "plots-purchased" "plots-sold" "1")
file-close
file-open "general-info.txt"
file-write (list "1" "simulation" "year" "dead" "retired-exit" "voluntary-exit" "forced-exit" "plots-sold"
"plots-unsold" "reservation-not-met" "credit-constrained" "farmers with generation > 1" "1")
file-close
file-open "mean-info.txt"
file-print (list "1" "simulation" "year" "mean-D/A" "mean-land-value" "mean-capital-value" "mean-cash" "mean-
debt" "Mean-Acres-Cropped" "Mean-Skill" "Mean-NCFBI/Acre" "1")
file-close
file-open "retiree-info.txt"
file-print (list "1" "simulation" "year" "who" "age" "breed" "type-of-exit" "generation" "skill" "attitude" "plots-
owned" "average-soil-quality" "risk-aversion" "debt" "asset-value" "years-neg-ncfbi" "1")
file-close
file-open "winner-details.txt"
file-print (list "1" "simulation" "year" "current-plot-bid-on" "bidders" "auction-winner" "auction-seller"
"reservation-price"
"distance- to-plot-bid-on" "max-bid" "max-bid-credit-constraint" "value-of-land-bid-on" "bid"
"current-bid"
"abs-max-bid" "price-paid" "credit-constrained?" "buyer-gain" "seller-gain" "times-bid" "won-last" "1")
file-close

end

```